LOCATION-ALLOCATION MODELS FOR RELIEF DISTRIBUTION AND VICTIM EVACUATION AFTER A SUDDEN-ONSET NATURAL DISASTER

By

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ABSTRACT

Quick response to natural disasters is vital to reduce loss of and negative impact to human life. The response is more crucial in the presence of sudden-onset, difficult-to-predict natural disasters, especially in the early period of those events. On-site actions are part of such response, some of which are determination of temporary shelters and/ or temporary medical facility locations, the evacuation process of victims and relief distribution to victims. These activities of last-mile disaster logistics are important as they are directly associated with sufferers, the main focus of any alleviation of losses caused by any disaster.

This research deals with the last-mile site positioning of relief supplies and medical facilities in response to a sudden-onset, difficult-to-predict disaster event, both dynamically and in a more coordinative way during a particular planning time horizon. Four mathematical models which reflect the situation in Padang Pariaman District after the West Sumatera earthquake were built and tested. The models are all concerned with making decisions in a rolling time horizon manner, but differ in coordinating the operations and in utilization of information about future resource availability. Model I is a basic model representing the "current practice" with relief distribution and victim evacuation performed separately and decisions made only considering the resources available at the time. Model II considers coordination between the two operations and conducts them with the same means of transport. Model III takes into account future information keeping the two operations separate. Model IV combines the features of Models II and III. The four models are approached both directly and by using various heuristics.

The research shows that conducting relief distribution and victim evacuation activities by using shared vehicles and/or by taking into account future information on resource availability improves the "current practice". This is clearly demonstrated by the experimental results on small problems. For large problems, experiments show that it is not practical to directly solve the models, especially the last three, and that the solution quality is poor when the solution process is limited to a reasonable time. Experiments also show that the heuristics help improve the solution quality and that the performances of the heuristics are different for different models. When each model is solved using its own best heuristic, the conclusions from results of large problems get very close to those from small problems. Finally, deviation of future information on resource availability is considered in the study, but is shown not to affect the performance of model III and model IV in carrying out relief distribution and victim evacuation. This indicates that it is always worthwhile to take into account the future information, even if the information is not perfect, as long as it is reasonably reliable.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

In this chapter, the background of the current research is presented. This is followed by a section which identifies the research problem more clearly. The scope of the research follows, which is needed in order for the research to be specific and focused. Following the research scope, general objectives of the current research are presented. An outline of the thesis is presented afterwards. The chapter concludes with thesis contributions.

1.1 Research Background

A disaster is highly likely to lead to severe problems, including extensive human misery and physical losses or damage. The frequency of both natural and manmade disasters is expected to grow over time, affecting millions of people.

In the sense of natural disasters, there was an increasing trend of occurrences from year 1900 to 2011. Those events killed millions of people, affected millions of others and caused US$ billions in economic damage. For the same period, most natural disasters took place in developing countries as well as the least developed countries. Equally, the majority of the human victims resulting from natural disaster occurrences in the same period were located in developing and least-developed countries.

Regarding their occurrence and/or impact, natural disasters can be classified as either sudden-onset or slow-onset. Natural disasters in the first category are characterised by their rapid arrival and impact, whereas those in the latter class arise slowly with slow impact. Natural disasters can also be classified in accordance with their predictability, i.e. either predictable – with a certain degree of accuracy – or not. Considering these two ways of categorisation, it is possible to have natural disasters with sudden-onset, difficult-to-predict occurrence. Earthquakes are an example of this type of natural disaster. Slow-onset, easy-to-predict is another category of natural disasters, an example of which is drought.

In order to reduce loss and negative impact to human life, it is vital to respond quickly to natural disasters. It usually incorporates - to name a few - the provision of disaster logistics, the evacuation process of threatened populations, and fatality management. The response is even more crucial in the presence of sudden-onset, difficult-to-predict natural disasters, especially in the early period of those events.

Disaster logistics itself consists of various activities. These include the activation of emergency operations centres, the establishment of shelters and the provision of mass care service, the provision of emergency rescue and medical care service, and the delivery of food, medicine, tents, sanitation equipment, tools and other necessities to disaster sufferers.

1.2 Research Problem Identification

The occurrence of a natural disaster leads to victims, infrastructure damage and psychological impacts, respectively. Victims of a natural disaster can be classified as wounded victims and injury-free sufferers. In certain circumstances, a natural disaster occurrence also causes death. Impacts on infrastructure range from damage to telecommunications to damage to housing, schools, and government buildings. It is also not uncommon that existing medical facilities are impacted by a natural disaster in such ways that their capability to provide medical services is reduced significantly. Additionally, it is inherent in any event declared as a disaster that the impact of the event exceeds the capacity of the affected societies to cope.

The appearance of a natural disaster – particularly that with sudden impact and which is hard to predict - needs to be responded to with on-site actions, some of which are as follows: (1) Identification process of injuries, injury-free victims, and dead victims/ human remains, (2) First aid for the wounded victims, (3) Determination of temporary shelters and/ or temporary medical facility locations followed by their establishment, (4) Evacuation process of the victims, and (5) Relief distribution to the victims. These activities of last-mile disaster logistics – i.e. disaster logistics at the final stage of the disaster logistical chain - are important as they are directly associated with the sufferers, the main focus of any alleviation of losses caused by any disaster.

The establishment of temporary facilities –such as temporary medical centres/ facilities, temporary intermediate distribution centres and/ or temporary shelters - is an important part of response to a last-mile sudden-onset, difficult-to-predict natural disaster. Temporary medical centres are needed to reduce congestion in existing emergency units. They are also needed to reduce delay in providing health care service for the victims. Intermediate distribution centres are needed to support the distribution process of logistics to disaster areas. Temporary shelters, if necessary, are crucial in providing temporary housing for the victims. For example, victims' houses may be destroyed or the risk of remaining in residence too great.

The evacuation process of the survivors is a very important last-mile action after any sudden-onset, difficult-to-predict natural disaster. In this type of response, injured victims are transported either to operational existing medical centres or to temporary medical facilities. If necessary, injury-free victims may go or be transferred to temporary shelters. When removed from disaster areas, human remains are generally transported to hospitals – either permanent or temporary - for autopsy.

Another equally important last-mile action following sudden-onset, difficult-to-predict natural disasters are the distribution of relief to sufferers. Commodity supplies need to be delivered to those who refuse to leave or be evacuated from the affected sites. The evacuees in temporary shelters, if any, also need to be supplied with food, water, tents, tarpaulins, clothes and the like.

Responses such as those mentioned above could be under single authoritative bodies or, more likely, involve various organisations in charge. These organisations may serve autonomously or under a particular rule of coordination. Within the context of Indonesia, for instance, the Ministry of Social Affairs and its derivatives at lower levels of governmental structure is responsible for the provision of temporary intermediate distribution centres and/ or temporary shelters and the supply of relief goods to disaster victims. Still in the same country, the services to injured victims (including the establishment of temporary medical centres/ facilities and their evacuation to medical facilities) are carried out by, among others, the Ministry of Health and its derivatives at various levels of governmental organisation. The National Board for Disaster Management and its derivatives, in the meantime, serve as coordinating governmental bodies in the event of disasters. With regard to the response phase of managing the disasters, the last body has a command power in coordinating other parties (including those from other countries and/or not-for-profit relief organisations) involved in disaster management.

In responding to a particular disaster event at on-site level, availability of resources such as temporary medical facilities that need to be deployed or means of transport for distributing the relief and/or evacuating the victims are important factors that needs to be considered. Therefore, it is crucial to have information on resource availability characteristics to hand. This includes the fact that the resources available at different time points vary, in other words, the information on resources is dynamic in nature. It is not unusual that the information on resource availability throughout the period of the disaster relief operation might be known at the beginning of the disaster response with relatively high accuracy. This, for instance, is due to the reality that those resources are provided by other parties and the parties are able to let the coordinating authoritative body know about the resource availability in advance.

With regards to all the aforementioned factors and features, it might be valuable to conduct the last-mile site positioning of relief supplies and medical facilities in response to a particular sudden-onset, difficult-to-predict disaster event dynamically and in a more coordinative way during a particular planning time horizon. The coordinative way may refer to the resource sharing of the relief distribution and victim transportation or might be related to the inclusion of information on resource availability during the planning horizon. In this sense, there are at least three different potential methods of last-mile positioning to consider: (1) dynamically conducting relief distribution and victim evacuation with the same means of transport, (2) dynamically carrying out relief distribution and victim transportation separately taking into account information on resource availability in upcoming periods, and (3) combining the first two into one action.

These three approaches can be evaluated and compared using a performance criterion derived from a desire to reduce loss of, and negative impact on, human life, the main purpose of any response to the upheaval caused by a disaster.

1.3 Research Scope

This research is limited by the following scope:

1. Natural disasters under study are characterized by their sudden, difficult-to-predict onset, whereas slow-onset/impact natural disasters (such as famine and drought) are excluded.

2. The victims are categorised into injured victims and injury-free sufferers and are located in certain disaster areas. The process of classifying the victims and the provision of first aid to them are excluded.

3. Due to the emergency nature of sudden-onset natural disaster response, costs are not the major concern. The research will therefore take no account of costs incurred in the process of achieving an optimal solution.

4. This study is merely based on a positivist point of view; it does not deal with the matter of achieving a "thick description" – i.e. "... the researcher's task of both describing and interpreting observed social action (or behavior) within its particular context" (Ponterotto, 2006) - of natural disasters.

1.4 General Research Objectives

This research is carried out to meet the following general objectives:

1. To produce mathematical models which help to optimise the decisions on distributing relief, evacuating victims, and determining temporary site

allocations following a sudden-onset, difficult-to-predict natural disaster occurrence;

2. To obtain general insights about the performance of the mathematical models; and
3. To improve the process of distributing relief and evacuating victims soon after the occurrence of a sudden-onset, difficult-to-predict natural disaster.

1.5 Outline of Thesis Report

A brief synopsis of each chapter follows.

Chapter 1: Introduction

Chapter 1 provides a background to the research, research problem identification, research scope, general research objectives, and outline of the thesis.

Chapter 2: Literature Review

This chapter reviews previous research papers and other documents that are relevant to the current research. The review covers a variety of issues, but is mainly focused on disaster logistics and previous work on disaster logistics optimisation. The last part of this chapter is concerned with research significance, and explains how the current research fills in research gaps found in the literature and hence explains its significance.

Chapter 3: Mathematical Models

Motivated by the research problem under concern, four different mathematical models are presented. The first model tries, in many aspects, to represent the problem of “real practice” as it was found during the fieldwork. Three other mathematical models which are intended as improvements to the “real practice” model are also formulated.

Chapter 4: On Model Testing with Computational Experiments

Computational experiments are performed to test the operability and performance of the models developed in Chapter 3. Data obtained from the fieldwork following the West Sumatera earthquake are used as parameter inputs. Analysis of the experimental results includes statistical significance and practical significance and is used to compare the relative performance of the four models using model I as a baseline.

Chapter 5: On Heuristics

In order to obtain additional insights into the performance of the four models on larger test problems, several heuristics are applied to the problems under consideration. The results of the application of the heuristics are analysed and discussed. Finally, a comparison on the performance of each of the models with and without the heuristic approaches is carried out and used to advise if and when it is better to utilize the model as is or to apply a heuristic.

Chapter 6: Conclusions

The final chapter provides overall conclusions, highlights research limitations and considers future research directions in this area.

1.6 Thesis Contribution

This research addresses location-allocation problems in relief distribution and victim evacuation after a sudden-onset, difficult-to-predict natural disaster and makes contributions in the following areas:

1. Detailed review of problems and related previous research in disaster logistics.

2. Development of mixed integer programming (MIP) models to optimise the site positioning of relief supplies and medical facilities in response to disaster occurrences dynamically and in a more coordinative way.

3. Development of several heuristics to solve the abovementioned site positioning optimisation problem efficiently.

4. Testing of these models and heuristics to evaluate the benefits of taking a coordinative approach and utilising future information.

CHAPTER 2

LITERATURE REVIEW

This chapter focuses on literature relevant to the research under concern. In order to be precise, a definition of disaster is needed. It is also important to have a clear scope about which type of disaster the current research deals with. A closer look at disaster trends and its impact supports how important disaster management is, meaning that a short overview on the disaster management cycle is necessary. Logistics within a disaster context is the issue of the current research and, therefore, it is essential to consider this area. The current research proposes to carry out site location in a more coordinative way, and thus coordination in the context of disaster needs to be outlined. Performance of the proposed approaches is a key element of this research and hence a short outline of performance measures and disaster logistic optimisation is provided. There follows a review of research work on the optimisation of disaster logistics – especially those which include location aspects – another key element of the research presented in this thesis. How the facilities are deployed is as important as other issues and is presented in the last part of this chapter. All of the sections in the chapter give clear evidence that research gaps exist and that the current research is important and relevant.

2.1 Definition of Disaster

Disaster has been defined in many different ways. Indeed, there is no precise or standardised definition for a disaster (Eshghi and Larson, 2008; Guha-Sapir *et al.*, 2004). For these reasons, the following paragraph presents various definitions on disaster from a variety of sources. Several common terminologies in the definitions are then extracted, and a proposed definition employed in the thesis is provided at the end of this section.

The United Nations (UNISDR, 2009) and the Asian Disaster Reduction Center (ADRC, 2013) define disaster as "a serious disruption of the functioning of society, causing widespread human, material or environmental losses which exceed the ability of affected society to cope using only its own resources". In its complete form, the Emergency Events Database (EM-DAT) defines disasters as "a situation or event which overwhelms local capacity, necessitating a request to the national or international level for external assistance, or is recognized as such by a multilateral agency or by at least two sources, such as national, regional or international assistance groups and the media" (Guha-Sapir *et al.*, 2004). The International Federation of Red Cross and Red Crescent Societies (IFRC) defines a disaster as "... a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources…" (IFRC, 2013). Emergency Management Australia (EMA) defines disaster as "a serious disruption to community life which threatens or causes death or injury in that community and/or damage to property which is beyond the day-to-day capacity of the prescribed statutory authorities and which requires special mobilization and organization of resources other than those normally available to those authorities" (EMA, 1998). Below *et al.* (2007) propose "an accumulation of widespread losses over multiple economic sectors, associated with a natural hazard event, that overwhelms the ability of the affected population to cope" as a definition of a disaster. Keller and DeVecchio (2012) describe disaster as a hazardous event taking place in a certain region over a limited period.

From those various definitions, it is apparent several terminologies are commonly shared. These include event, losses, affected population and beyond-capacity or beyond-ability. From these shared terminologies, the thesis defines disasters as those events that cause losses to the affected population to a degree which is beyond the ability of the population to handle.

2.2 Disaster Types

Disasters can be classified in several ways. These ways include, to name a few, causes of disaster, speed of disaster arrival, arrival time and location of disaster (Apte, 2009; Apte and Yoho, 2011) and a combination of causes of disaster and speed of disaster arrival (Van Wassenhove, 2006). Disaster can also be classified according to numbers of victims and affected areas (Gad-El-Hak, 2008).

Regarding their causes, EM-DAT (see, for example, Guha-Sapir *et al.* (2013); EM-DAT (2009b)) andFischer (2008) classify disasters into two different categories: natural and technological. The natural disasters are further distinguished into biological, geophysical, hydrological, meteorological and climatological disasters (EM-DAT, 2009a). Earthquakes, floods, tornadoes, volcanoes and tsunamis are examples of the first category of disasters (see EM-DAT (2009a) and Fischer (2008)), whereas nuclear accidents and mass transportation accidents, on the other hands, are examples of the second category of disasters (Fischer, 2008).

An example of classification of disasters with respect to their arrival time is, for instance, found in Coppola (2007). The author divides disasters into sudden-onset disasters and "creeping" ones. According to him, sudden-onset disasters often arise with little, or even without, warning, whereas "creeping" disasters can exist for a long time period. Earthquakes, tsunamis, volcanoes, landslides, tornadoes and floods are examples of the first category of disasters. Examples for the second category include drought, famine, the AIDS epidemic and erosion.

Van Wassenhove (2006) proposes a classification scheme (see Table 2.1) to understand disasters. According to him, disasters can be classified by using causes of disasters and arrival time. With respect to this way of classification, a particular disaster falls into one of sudden-onset natural disasters, sudden-onset man-made disasters, slow-onset natural disasters or slow-onset man-made disasters.

Table 2.1 Categorisation of disasters based on van Wassenhove (2006)

	Natural	Man-made
Sudden-onset	Earthquake, hurricane, tornadoes	Terrorist attack, *coup d'état*, chemical leak
Slow-onset	Famine, drought, poverty	Political crisis, refugee crisis

Regarding its scope in terms of sufferer number and/ or geographic areas affected, Gad-El-Hak (2008) distinguishes disasters into five categories as can be seen in Table 2.2.Using the table, an earthquake disaster that takes place on a 500 km^2 area and which affects the overall 100.000 inhabitants of the area is classified as a gargantuan disaster of which the scope is V.

Table 2.2 Disaster scope in terms of number of victims and/ or geographic areas affected (source: Gad-El-Hak (2008))

Scope	Category	No. of sufferers		Geographical areas affected
Scope I	Small disaster	< 10 persons	Or	< 1 km^2
Scope II	Medium disaster	10-100 persons	Or	1-10 km^2
Scope III	Large disaster	100-1,000 persons	Or	10-100 km^2
Scope IV	Enormous disaster	1,000-10^4 persons	Or	100-1,000 km^2
Scope V	Gargantuan disaster	> 10^4 persons	Or	> 1,000 km^2

It is also possible to distinguish a particular disaster according to its arrival predictability. Weather-related disasters such as hurricanes, wind storms, heavy localized rain or snowfall, and severe storms, heat waves, droughts, regional heavy precipitation, and extreme cold spells are usually predictable with a certain degree of accuracy (Dudhia, 2008). On the other hand are disasters of which arrival are unpredictable or hardly predictable, such as earthquake, terror attacks, and hazardous material release (see, for instance, Hsu and Peeta (2012) and Sayyady and Eksioglu (2010)).

This thesis uses a combination of the abovementioned disaster classifications to determine disaster types. Padang Pariaman District – from which most parameter inputs of all models in the thesis is taken -, in particular, has a total area of 1,328.79 km^2 with a total population of 390,226 people (data in year 2008; see BPS (2009)). An earthquake that took place in West Sumatera Province on September 30, 2009 heavily affected the district. The problem under study, therefore, is in the context of a sudden-onset, gargantuan, difficult-to-predict natural disaster. It is necessary to mention, however, that the approach proposed in the current research can also be applied to other sudden-onset disasters falling into a different scope such as the flash flood that took place in several villages in

Jember District in 2006, the tsunami in Pangandaran Beach, West Java, in 2007 or the Mount Kelud eruption that took place in February 2014, all of which fall into the enormous disaster category.

2.3 Trends in Disaster Occurrences and Their Impact

Lichterman (1999) predicts that frequency of disasters and their effects seem to be increasing. This prediction is confirmed by a review of various related published sources from 1900-2005 by Eshghi and Larson (2008). Both natural and man-made disasters are likely to raise another five-fold over the next fifty years (from the year 2005) due to environmental degradation, rapid urbanization and the spread of HIV/AIDS in the less developed world (Thomas and Kopczak, 2005b). By looking at the EM-DAT database (EM-DAT, 2013b), it is also obvious that there is an increasing trend in the occurrences of natural disasters from 1900 to 2011. Until 2004, over 90 percent of natural disasters occurred in developing countries (UNISDR, 2004). By processing data provided by EM-DAT, UNISDR shows that slightly more than 60% of natural disaster events during the period of 2002-2012 took place in Asia (UNISDR, 2013a).

Even though the total number of people killed by natural disasters from 1900 to 2011 shows a decreasing figure, the number of affected people and the economic loss caused by natural disasters suggest an opposite profile. With regard to 2011 alone, CRED (Centre for Research on the Epidemiology of Disasters) (see Guha-Sapir *et al.* (2012)) reports that there were 332 natural disaster occurrences (excluding biological disasters) with 30,773 persons killed, 244.7 million others affected and approximately US$ 366.1 billion of economic damage. The same figures in 2012 as presented by UNISDR (UNISDR, 2013b), meanwhile, are 310 natural disaster events, 9,330 dead victims, 106 million affected people and around US$ 138 billion economic loss. With regard to technological disasters, figures on their occurrences and people killed rose significantly from the 1970s to 2011 (EM-DAT, 2013c). Figures on economic loss caused by the disasters from the 1980s to 2011, similarly, demonstrates a considerable increase (EM-DAT, 2013a).

2.4 Disaster Management

Disaster management can be seen as “the body of policy and administrative decisions, the operational activities, the actors and technologies that pertain to the various stages of a disaster at all levels” (Lettieri *et al.*, 2009). The term emergency management is usually used in place of disaster management (see, for instance, UNISDR (2009) and Moe and Pathranarakul (2006)). Meanwhile, disaster operations can be considered as the set of activities that are performed before, during, and after a disaster which are aimed at preventing loss of human life, reducing its impact on the economy, and returning to a normal situation (Altay and Green, 2006). Using the terminology of disaster relief operations (DRO) as a substitute for disaster operations, Pujawan *et al.* (2009) state that DRO consists of a variety of activities such as assessing demands, acquiring commodities, finding out priorities as well as receiving, classifying, storing, tracing and tracking deliveries.

Disaster management can be divided into four, inter-connected phases (see, for example, Altay and Green (2006), Coppola (2007), Lodree *et al.* (2012), Miller *et al.* (2005) and Tomasini and van Wassenhove (2009)): mitigation, preparedness, response, and recovery (or rehabilitation). The following paragraphs give a brief explanation of each disaster management phase.

2.4.1 Disaster Mitigation

Mitigation is the application of measures for either avoiding or lessening the possibility or the consequence (or consequence component) of a disaster arrival, or both (see, for instance, Coppola (2007), Altay and Green (2006) and Lodree *et al.* (2012)). Occasionally entitled prevention or risk reduction (Coppola, 2007), mitigation “treats” the disaster in such a way that the disaster occurrence affects people to a lesser extent (Coppola, 2007). Mitigation activities give attention to long-term solutions and, in general, are the most costly options in disaster management (Lodree *et al.*, 2012). Examples of mitigation activities are, to name a few, construction of barrier systems to deflect disaster forces, zoning and land use control to avoid occupation of high hazard areas, environmental control, behavioural adjustment and controls on building reconstruction following disaster events (see, for instance, Altay and Green (2006) and Coppola (2007)).

2.4.2 Disaster Preparedness

Preparedness involves activities taken in advance of a disaster occurrence to provide adequate response to and to recover from the effects of the disaster arrival (see, for example, Coppola (2007), Altay and Green (2006) and Lodree *et al.* (2012)). It aims at knowing what to do and how and being properly equipped following a disaster onset (Coppola, 2007). Unlike disaster mitigation, disaster preparedness gives focus on short-term activities (Lodree *et al.*, 2012). Examples of activities in the disaster preparedness stage include: setting up large-scale evacuation plans, securing disaster relief supply items (Lodree *et al.*, 2012), relevant training for response personnel or related citizens and establishment of emergency operation centres (Altay and Green, 2006). Another example is the provision of vehicles and equipment needed in the response phase (Altay and Green (2006); Coppola (2007)).

2.4.3 Disaster Response

Among the four functions of disaster management, the response phase is the most complex activity (Coppola, 2007). Disaster response can be defined as the employment of a set of measures during the initial occurrence of certain disastrous events, including those to save casualties' lives and prevent further property damage (see, for example, Barbarosoğlu and Arda (2004) and Coppola (2007)). It is usually performed as part of a previously determined disaster response plan (Altay and Green, 2006) and starts as soon as a particular disaster is about to happen and ends once the emergency is declared to be over (Coppola, 2007). Disaster response incorporates the evacuation process of threatened populations (Tierney *et al.* (2003); Altay and Green (2006); Yi and Kumar (2007); Chiu and Mirchandani (2008)), the activation of emergency operations centres, the establishment of shelters and the provision of mass care services, the provision of emergency rescue and medical care services, fire fighting (Altay and Green, 2006) and fatality management (Altay and Green (2006); Coppola (2007)), to name a few.

2.4.4 Disaster Recovery

Recovery involves long-term actions carried out after the instantaneous impact of the disaster has passed to get the victims' lives back to pre-disaster conditions and to lessen the risk of the same misfortune (Coppola (2007); Lodree *et al.* (2012); Altay and Green (2006)). It generally starts once the response phase has been completed (Coppola, 2007). Examples of disaster recovery include debris removal, rebuilding of dwellings, provision of temporary housing or shelter, and business restoration (see, for example, Coppola (2007), Lodree *et al.* (2012) and Altay and Green (2006)).

The current research takes into account issues of location positioning, relief distribution and victim evacuation in the aftermath of a sudden-onset, massive, and unpredicted natural disaster. It is clear, therefore, that disaster response is the most relevant phase of disaster management to the research. The response to such a disaster, as already explained, also relies on a previously established response plan. This means that the research is also closely related to the preparedness phase of the disaster life cycle.

Logistics plays an important part in all phases of disaster management. It is especially true in disaster preparedness and disaster response, the phases to which the thesis is mostly related. Location positioning, relief distribution and victim evacuation are all logistics-related issues. The logistical issues within disaster management are therefore explored and presented in the following section. Research on logistics optimisation in preparedness and response phases of disaster management is presented in Section 2.8, and is focused on aspects such as location, resource allocation, relief distribution and victim transportation.

2.5 Logistics in Disaster Management

2.5.1 Definition and Scope of Logistics

Logistics can be defined as follows (Sheu, 2007a):

> *"Logistics is the process of planning, implementing, and controlling the efficient, effective flow and storage of goods, services and related information from the point of origin to the point of consumption for the purpose of conforming to customers requirements at the lowest total cost."*

Logistics system operation consists of network design, information, transportation, inventory, warehousing, material handling and packaging (see Wu and Huang (2007)). Network design itself can be seen as consisting of the following activities (Goetschalckx, 2008): (1) establishing the appropriate quantity of distribution centres (DCs); (2) setting up the location of each DC; (3) allocating customers to each DC; (4) allocating appropriate commodities to each DC; and (5) determining the throughput and storage capacity of each DC.

2.5.2 Characteristics of and Activities in Logistics within the Disaster Context

Many different terms are used to describe the application of logistics in the disaster context. These include disaster logistics (see, e.g., Van Wassenhove (2006)), disaster relief logistics (see, for instance, Clay Whybark (2007) and Schulz and Blecken (2010)), humanitarian logistics (Kovacs and Spens, 2011; Kovács and Spens, 2007, 2009, 2011; Tatham and Kovács, 2010), relief logistics (e.g. Hsueh *et al.* (2008)), emergency logistics (see, for example, Sheu (2007a), Caunhye *et al.* (2012) and Tovia (2007)), emergency relief logistics (e.g. Pettit and Beresford (2005) and Lei (2007)), humanitarian relief chain (e.g. Beamon and Balcik (2008); Balcik *et al.* (2010); Charles and Lauras (2011)), humanitarian relief supply chain (e.g. Russell (2005), Falasca and Zobel (2011) and Ben-Tal *et al.* (2011)), disaster supply chain (see, e.g., Boin *et al.* (2010)), disaster relief supply chain (see, for example, Clay Whybark *et al.* (2010) and Day *et al.* (2009)) and humanitarian and disaster relief supply chain (e.g. Day *et al.* (2012)). The terminologies all refer to similar activities and components henceforth referred to as disaster logistics within this thesis.

Logistics in the disaster context has its own unique characteristics, especially with respect to its demand and supply, ultimate goals and environmental factors (Balcik and Beamon, 2008). It is apparent that the goods, materials, related information and services in the disaster context are present with uncertainty (Balcik and Beamon, 2008), are needed under emergency conditions (Sheu, 2007a), are demanded in huge amounts and with very short lead time (Balcik and Beamon, 2008), and, therefore, they are critical (Apte, 2009). Unlike commercial logistics, the main purpose of disaster logistics is to reduce the beneficiaries' suffering (Thomas and Kopczak, 2005a). In general, disaster logistics take place in a complex environment (see, e.g. Day *et al.* (2012) or Van Wassenhove (2006)).

Disaster logistics consists of a variety of operations and activities. These include, but are not limited to, asset prepositioning and resource allocation, temporary site selection, relief distribution, victim evacuation and inventory management (see, for instance, Holguín-Veras *et al.* (2012a); Apte (2009, ch. 4 and Conclusion); Yi and Özdamar (2007)).

2.5.3 Importance of Disaster Logistics

Previous sections have already illustrated the vital role that logistics play in emergency management. Sheu (2007a) declares that, due to the possibility of disaster occurrences anytime around the world with huge effects, disaster logistics management has become an important global concern. Disaster logistics is even more crucial because it can be one of the most expensive elements of a relief effort (Thomas and Kopczak, 2005b), where 80% of cost is associated with logistics (Van Wassenhove, 2006). People affected by disasters, deprived of food, housing, livelihood and other means of supporting themselves need the delivery of food, medicine, tents, sanitation equipment, tools and other necessities (Clay Whybark, 2007). The timely delivery of important goods after a disaster event is crucial (Boin *et al.*, 2010). The science of logistics and supply chain management is becoming more vital for humanitarians (Van Wassenhove, 2006), and "the subject of disaster management is an absolutely fascinating one that is growing in importance" (Van Wassenhove, 2003). The importance of disaster logistics also stems from its contribution to the effectiveness and speed of response for humanitarian programs and its role in supporting repository data for post-event knowledge (Thomas and Kopczak, 2005b).

The vital role of disaster logistics is also supported by disaster events from the field. This is indicated, for instance, by Oloruntoba (2005) and Thomas (2006) with regard to the 2004 Indian Ocean tsunami, Portilla *et al.* (2010) and Holguín-Veras *et al.* (2013) with respect to the 2010 Haiti earthquake and Norio *et al.* (2012) concerning the 2011 Eastern Japan tsunami.

2.5.4 Disaster Logistics and Its Potential Improvement

McEntire (1999) states that disaster studies must discover ways to improve the provision of relief after a disaster hits. Regarding the relief of the Indian Ocean tsunami, the humanitarian organizations providing relief acknowledged that relief supply can and needs to be faster and more efficient (Thomas, 2005). Together with hurricane Katrina, the Indian Ocean tsunami gives evidence that there is a lack of ability to connect the aid provided with the aid received (Thomas, 2005), regardless of the unprecedented amount of relief provided during these two misfortunes.

The potential improvement in disaster logistics could come in a variety of ways. Perry (2007), for instance, accentuates the availability of logistician cadres as a key element of disaster response, as part of needs assessment and for procuring, transporting, and distributing relief provisions. Good logistics planning as a key to the success of an emergency program is suggested by Davis and Lambert (2002). Furthermore, the development of new technology for track/trace and disaster relief supply chains is proposed as one way to improve the delivery of humanitarian relief (Baluch, 2007). In the context of the participation of non-governmental organizations (NGOs) in worldwide emergencies (e.g. volcanic eruptions, earthquakes, floods, war), Beamon and Kotleba (2006) point out that the capability of an NGO’s supply chain and logistics operations directly influences the success of a relief effort. Pujawan *et al.* (2009), meanwhile, propose information visibility, coordination, accountability, and professionalism as successful requirements of logistics for DRO.

The difficulties of logistics management in the disaster context tend to be increasing with the presence of a variety of organisations addressing different needs, mandates, capacity and logistics capability and arriving at different time points, which are discussed in the following section.

2.6 Coordination in the Disaster Management Context

When a disaster strikes, it is common that a variety of organisations get involved (Balcik *et al.*, 2010). Their involvement is not always in the same time frame (see, for instance, Telford and Cosgrave (2006) with regard to the 2004 Indian Ocean tsunami, Abolghasemi *et al.* (2006) on arrivals of international response to the 2003 Bham earthquake and Norio *et al.* (2012) concerning international assistance to the 2011 Eastern Japan tsunami). Additionally, a disaster frequently takes place where resource scarcity exists (Balcik *et al.* (2010); Najafi *et al.* (2013)). All of these lead to increasing complexity of management and calls for good coordination (Coppola (2007); Baldini *et al.* (2012)). In the disaster context, coordination has been defined as “the relationships and interactions among different actors operating within the relief environment” (Balcik *et al.*, 2010).

Effectiveness in responding to disaster arrivals is the main objective of coordination (Akhtar *et al.*, 2012). A solid coordination is proven to be able to lessen losses arising from disasters (see, for instance, Prizzia (2008)) and serves as a critical success factor in disaster management (Moe and Pathranarakul, 2006). Regarding the response phase of the disaster management life cycle, well-coordinated response is vital for its effectiveness (Rosen *et al.*, 2002). Indeed, lack of coordination is found as one cause, along with others, of failure of the response (Thévenaz and Resodihardjo (2010); Cigler (2007); Eikenberry *et al.* (2007) with respect to Hurricane Katrina, 2005).

Coordination might take place vertically (i.e. amongst entities at different levels of the disaster relief chain) or horizontally (i.e. amongst entities at the same level of the disaster relief chain) (Balcik *et al.*, 2010). The need for coordination in disaster management can take place at international level, national level and/ or field level (Tomasini and van Wassenhove, 2009), depending on the scope of the disaster. With respect to the disaster life cycle, coordination can be by command, by consensus, or by default (Tomasini and van Wassenhove, 2009).

As mentioned above, the involvement of various agencies in a disaster response takes place at different periods. Consequently, resource supplies included in the response are not always available at the same time points. This includes vehicles (see, for instance, Pedraza Martinez *et al.* (2011)) and medical facilities (see, for example, Abolghasemi *et al.* (2006)). The vehicles need to be dispatched (see, for example, Jotshi *et al.* (2009)) and the medical facilities, frequently, have to be positioned (see, e.g., Merin *et al.* (2010) and Kreiss *et al.* (2010)). Along with the fact that the resources are frequently limited, the utilisation of the resources needs to be well-coordinated, two of which activities are resource sharing (see, e.g., Chen *et al.* (2008), Nolte *et al.* (2012) and Kapucu *et al.* (2009)) and the inclusion of confirmed and anticipated data on resource availability in the current disaster management plans and measures (see, for example, Ozdamar and Yi (2008), Yi and Özdamar (2007) and Yi and Kumar (2007)).

Regarding the South Asian earthquake in 2005 (see Akhtar *et al.* (2012)), it was found that tangible resources (finance, technology, and people), intangible resources (leadership, relevant experience and education, relationship management skills, research abilities, and performance measurement skills) and extra effort (extra time and hard work) determine the success of coordination. With respect to the Fort Worth tornado (March 28, 2000), political support, preparedness measures, networking and cooperative relationships, technology, and the nature and use of emergency operations centres were found to be key success factors of the given coordinated response (McEntire, 2002).

2.7 Performance Measures and Disaster Logistics

Performance measurement is needed in each of the disaster management stages in order to examine the present level of performance and to unearth aspects that are still open for improvement (Moe *et al.*, 2007).This also applies to disaster logistics as part of disaster management (see, for instance, Beamon and Balcik (2008) and Bolsche (2013)). Insight into logistical performance can be obtained in at least two ways: (1) by comparing the performance measures of different disaster logistical structures for different disaster events (see, for example, Gatignon *et al.* (2010) with regard to old and new supply chain structures of IFRC), or (2) by comparing the performance measures of different disaster logistical structures for a particular disaster (see, for example, Holguín-Veras *et al.* (2012b) with respect to different logistic structures following the Haiti earthquake).

Critical success factors in the disaster logistic management context have been proposed (see, for example, Pettit and Beresford (2009)). Several scholars, furthermore, have developed performance metrics for disaster logistics (see, e.g., Beamon and Balcik (2008), Davidson (2006), Schulz and Heigh (2009), Bolsche (2013), Santarelli *et al.* (2013) and Torabi (2013)).

Average and minimum response time (Beamon and Balcik (2008); Torabi (2013)), delivery date reliability (Santarelli *et al.,* 2013), goods-to-delivery time (Santarelli *et al.* (2013); Davidson (2006)), total amount of relief supplied to the victims (Torabi (2013); Beamon and Balcik (2008)), number of flawless deliveries (Torabi, 2013) and unsatisfied demands on goods (see, for instance, Ozdamar *et al.* (2004) and Lin *et al.* (2011)) are examples of the performance features, factors and measures of relief distribution. Total number of victims served (Liu *et al.*, 2010) and time needed or distance travelled for evacuation (Saadatseresht *et al.* (2009); Yuan and Wang (2009); Fang *et al.* (2011); Chiu *et al.* (2007)), injured victims transported to medical facilities (Kuwata and Takada, 2004) or simply victims evacuated (Chiu *et al.*, 2007) are examples of performance measures of victim evacuation. A combination of un-evacuated injured people and unsatisfied demand on commodities (see, for instance, Yi and Kumar (2007), Ozdamar and

Yi (2008), Ozdamar (2011) and Najafi *et al.* (2013)) is an example of a performance measure of joint relief distribution-victim transportation.

2.8 Problem Types in Disaster Logistic Optimisation

This section focuses on several problem types in combinatorial optimisation (see, for instance, Blum and Roli (2003), Blum (2005), Zlochin *et al.* (2004) on the subject of combinatorial optimisation) within the disaster logistic context using mathematical models as the main modelling methodology. For the reason of relevance to the current research, the problems presented are limited to those on the allocation of resources to particular places or demand points, how relief delivery or victim evacuation (including the route selection) is carried out, how particular sites are selected and how combined site location-routing in the disaster context is conducted. For the same reason, the research reviewed is mainly related to disaster preparedness and disaster response, the most relevant areas of research to this thesis. Four different problem types in disaster logistic optimisation are subsequently identified: (1) resource allocation problems, (2) relief distribution and/ or victim transportation, (3) location-allocation problems, and (4) location-routing problems. The following sub-sections explore these problem types in more detail, with particular emphasis on location-allocation and location-routing as these are more relevant to the current research.

2.8.1 Resource Allocation Problems

The resource allocation problem in general is the process of allocating resources to a variety of activities, projects or business units in order to optimise particular objectives subject to a set of constraints (Chaharsooghi and Meimand Kermani, 2008; Yin and Wang, 2006a, 2006b). The objectives could be profit maximisation or cost minimisation (Chaharsooghi and Meimand Kermani, 2008). When formulated as a mathematical programming problem, the objectives can be either linear or non-linear (Yin and Wang, 2006a). A considerable amount of research on resource allocation optimisation has been carried out within a disaster context, for example Fiedrich *et al.* (2000), Gong and Batta (2007), Zhu *et al.*

(2008), Lee *et al.* (2006), Altay (2012), Arora *et al.* (2010), Mert and Adivar (2010) and Adıvar and Mert (2010).

2.8.2 Relief Distribution and/or Victim Transportation

According to Chopra (2003), distribution can be seen as a series of steps to convey and stock up a product from the provider to a user in the supply chain. Relief distribution comprises three different elements: supply, demand and transportation (Tzeng *et al.*, 2007). Humanitarian aid distribution (see, for instance, Vitoriano *et al.* (2009), Vitoriano *et al.* (2010), Ortuño *et al.* (2010) and Balcik *et al.* (2010)) or relief aid distribution (see, for example, Balcik *et al.* (2008)) is sometimes used instead of relief distribution. Examples of relief distribution optimisation within a disaster context can be found in Barbarosoğlu and Arda (2004), Sheu (2007b), Tzeng *et al.* (2007), Liu and Zhao (2007), Chern *et al.* (2010), Wenxue and Zihui (2010) and Yan and Shih (2009). Research papers by Rottkemper *et al.* (2011), Rottkemper *et al.* (2012) and McCoy and Brandeau (2011), in the meantime, are examples of research which focus on relief distribution as well as other aspects of disaster logistics.

Evacuating disaster casualties from disaster areas to medical facilities is another issue arising after disaster occurrences. Disaster victim transportation can be seen as a process of distributing relief with the only difference that the object to be transported is people and not relief goods and has been researched by Chiu and Zheng (2007), Saadatseresht *et al.* (2009), Lu et al. (2003, 2005) and Jotshi *et al.* (2009) amongst others.

Considering the necessity of delivering relief and transporting victims, it is possible to handle these two activities simultaneously. Research papers by Yi and Kumar (2007) and Ozdamar and Yi (2008) are examples of this type of research on optimisation of relief delivery and/ or victim transportation.

One way of delivering relief to the victims or transporting victims from one place to another is by determining delivery/ evacuation routes. In this case, the relief distribution or casualty transportation is the same as the vehicle routing problem (VRP). In its most basic form (see, for example, Bulbul *et al.* (2008) and Laporte (2007)), VRP is concerned with the optimal delivery or collection routes for a limited number of identical vehicles with limited capacities from a central depot/ warehouse to a set of geographically scattered customers. Examples of research on VRP-type relief distribution optimisation within the disaster context include Haghani and Oh (1996) and Oh and Haghani (1997), Hwang (1999), Barbarosoğlu *et al.* (2002), Ozdamar *et al.* (2004), Berkoune *et al.* (2012), Balcik *et al.* (2008), Hsueh *et al.* (2008), Gong *et al.* (2009), Stepanov and Smith (2009), Jotshi *et al.* (2009), Yi and Kumar (2007) and Ozdamar and Yi (2008).

2.8.3 Location-Allocation Problems (LAPs)

As previously stated in Goetschalckx (2008), the location-allocation problem (LAP) (some papers use the term location problem instead) can be seen as part of distribution network design problems. Given the location of a set of customers with different demands, LAP is concerned with the selection of supply centres' positions dedicated to serving the customers as well as the decision of the allocation of the customers to supply centres, with both of them aimed at optimizing a given criterion (Hsieh and Tien, 2004). It is also assumed that there is no interaction among supply centres. The criterion can be single such as transportation costs (see, for example, Goetschalckx (2008); Zhou and Liu (2003); Manzini and Gebennini (2008)) or may comprise several aspects (see, for example, Mitropoulos *et al.* (2006)). Applications of LAP range from business-related sectors to public services environments (see, for instance, Smith *et al.* (2009)).

According to ReVelle and Eiselt (2005), LAP is characterised by four main elements: (1) customers, who are assumed to already exist, (2) facilities that will be situated, (3) a space in which customers and facilities are located, and (4) a metric that provides either distances or times between customers and facilities.

In the sense of the space in which the LAPs are modelled (Daskin, 2008; ReVelle *et al.*, 2008) or topological characteristics of the facility and demand sites (Jia *et al.*, 2007a), models on LAP can be divided into four different categories:

analytic models, continuous models, network models, and discrete models. In analytic models, demand is usually assumed to be distributed in some way over a service area and that facilities can be sited anywhere in the area. Continuous models typically assume that demand arises at discrete points in the area, whereas facilities can be located anywhere in the area. Network models assume that demand arises and facilities can be located only on a network comprised by nodes and links. Discrete models assume that demands as well as candidates for facilities locations are in discrete sets.

Location-allocation problem models can also be classified according to the nature of problem input parameters (see, for example, Owen and Daskin (1998), Current *et al.* (2001) and Boloori Arabani and Farahani (2012)). In this regard, there are four different types of LAP models: static, dynamic, deterministic and stochastic. Static LAP models assume that input parameters are static over time. In dynamic LAP models, input parameters vary over time and are assumed to be known. Deterministic LAP models assume that input parameters are known. When input parameters are uncertain, associated LAP models are called stochastic LAP models.

With respect to supply centres' capacity, LAP can be divided into capacitated and un-capacitated (Hsieh and Tien, 2004). Capacitated LAP refers to any LAP where the capacities of supply centres are fixed. When the capacities of each supply centre can be adjusted, the LAP is called an un-capacitated LAP.

Another criteria in classifying the LAP is the objective of the model (Jia *et al.*, 2007a). In covering models, the total quantity of sites is minimised while coverage to all demand points is provided or the coverage to demand points is maximised given a fixed number of sites. Minimising maximum distance is the main concern of *P*-centre models. The minimisation of total or average distance, on the other hand, is the main focus of *P*-median models.

Time horizon is another criterion for categorising LAP (Jia *et al.*, 2007a). With respect to this criterion, LAP models can be distinguished into static and dynamic LAP models. Static LAP models optimise the system performance by concurrently choosing all variable values. Dynamic LAP models consider different periods and all relevant information and data related to each of them, and the overall solution is obtained from each of these unique time intervals.

Research work on various LAPs is plentiful. The following papers provide several examples of this work: Hsieh and Tien (2004), Bischoff and Dächert (2009), Chan *et al.* (2008), Berman *et al.* (2007), Berman *et al.* (2008), Eben-Chaime *et al.* (2002), Zhou and Liu (2003, 2007), Wen and Iwamura (2008), Schmid and Doerner (2010) and Mitropoulos *et al.* (2006).

In addition, research on LAP has been carried out taking account of other aspects, for example inventory conditions or capacities of the facilities. The decisions with respect to all of these factors can be made simultaneously or in sequence order. Papers by Snyder *et al.* (2007), ÜSter *et al.* (2008), Yao *et al.* (2010) and Manzini and Gebennini (2008), to name a few, are examples of research on LAP with the inclusion of inventory level calculation. The presence of capacity calculation (e.g. of medical facilities) along with facility location and demand allocation aspects – and commonly found in health-related environment – can be found in, to name a few, Cho (1998), Segall (2000) and Harper (2005).

With regard to LAP in a disaster context, flow of ‘goods’ can be from the demand points (which represent points of origin) to facility sites (which function as points of destination) or vice versa. Included in the first category is research on LAP of which the main concern is victim transportation from disaster areas to medical facilities. The second type of research, on the other hand, contains research that gives attention to location of relief supply sites and demand allocation to sites.

The following paragraphs present an overview of research papers on the LAP in the context of disaster optimisation with respect to: types of disaster, disaster management phase to which the optimisation is devoted, input features, whether supply sites are capacity-constrained or not, objective of the model, main decisions, time horizon (whether it is single time period or multiple time period) and solution methods (i.e. exact methods or heuristics). Table 2.3 provides the related review in tabular form.

It should be noted that other decisions and/ or problem types in disaster logistics optimisation occasionally exist – such as inventory-related ones – and also need to be made. Unless included in the four abovementioned problem types, research on these types of problem and/ or decision is excluded from the overview as they are of minimal relevance to the thesis.

As mentioned previously, disasters can be classified as slow-onset, easy-to-predict disasters, slow-onset, difficult-to-predict disasters, sudden-onset, easy-to-predict disasters and sudden-onset, difficult-to-predict disasters. With regard to the research papers included on the LAP in the context of disaster optimisation, it was found that none of the abovementioned disaster categories were provided. The majority of research papers on LAP in the context of disaster logistic optimisation are concerned with disasters in general (see, for instance, Ablanedo-Rosas *et al.* (2009), Alcada-Almeida *et al.* (2009), Bozorgi-Amiri *et al.* (2013), Jia *et al.* (2007a), Kusumastuti *et al.* (2013), Rawls and Turnquist (2012)). Several research papers deal with sudden-onset disasters such as earthquakes or hurricanes (e.g. An *et al.* (2013), Balcik and Beamon (2008), Jia *et al.* (2007b) and Salmeron and Apte (2010)). Chang *et al.* (2007), Widener and Horner (2011), Galindo and Batta (2013) are examples of research that are concerned with sudden-onset, easy-to-predict disaster phenomena. Finally, sudden-onset, difficult-to-predict disasters are addressed by, for instance, Döyen *et al.* (2011), Edrissi *et al.* (2013), Hu *et al.* (2012), Li *et al.* (2011) and Mahecha and Akhavan-Tabatabaei (2012).

Another important issue is to which phase of disaster management the research is dedicated. Most of the papers under review deal with measures in the preparedness phase (see, e.g., Alcada-Almeida *et al.* (2009), Balcik and Beamon (2008), Chang *et al.* (2007), Galindo and Batta (2013), Hu *et al.* (2012), Jia *et al.* (2007b), Mahecha and Akhavan-Tabatabaei (2012) and Salmeron and Apte (2010)). Several papers (such as Li *et al.* (2011), Widener and Horner (2011),

Table 2.3 Research on disaster-related LAPs within disaster logistic optimisation

Author(s)	Disaster types	Phase	Input type	Supply capacity	Model objective	Main decisions	Time period	Solution method(s)
Ablanedo-Rosas *et al.* (2009)	General	Preparedness	Static	Un-capacitated	Covering	Location	Single	Exact
Alcada-Almeida *et al.* (2009)	General	Preparedness	Static	Capacitated	*P*-median	Location, victim transportation	Single	Approximate
An *et al.* (2013)	Sudden	Preparedness, response	Stochastic	Un-capacitated	*P*-median	Location, victim transportation	Single	Exact
Balcik and Beamon (2008)	Sudden	Preparedness	Stochastic	Capacitated	Covering	Location, inventory	Multi	Exact
Bozorgi-Amiri *et al.* (2013)	General	Preparedness, response	Stochastic	Capacitated	*P*-median, *P*-centre	Location, inventory, relief distribution	Single	Exact
Bozorgi-Amiri *et al.* (2012)	General	Preparedness, response	Stochastic	Capacitated	*P*-median, *P*-centre	Location, inventory, relief distribution	Single	Approximate
Campbell and Jones (2011)	General	Preparedness	Stochastic	Un-capacitated	*P*-median	Location, inventory	Single	Approximate
Chang *et al.* (2007)	Sudden, easy	Preparedness	Stochastic	Capacitated	*P*-median	Location, victim transportation	Single	Approximate
Chi *et al.* (2011)	General	Preparedness	Static	Capacitated	*P*-median	Location	Single	Approximate
Chowdhury *et al.* (1998)	Sudden	Preparedness	Stochastic	Capacitated	*P*-median	Location	Single	Exact
Dekle *et al.* (2005)	General	Response	Static	Un-capacitated	Covering	Location	Single	Approximate
Doerner *et al.* (2009)	Sudden, difficult	Preparedness	Stochastic	Un-capacitated	Covering, *P*-median	Location	Single	Exact, approximate
Döyen *et al.* (2011)	Sudden, difficult	Preparedness, response	Stochastic	Capacitated	*P*-median	Location, inventory, relief distribution	Single	Approximate

Table 2.3 Research on disaster-related LAPs ... (continued)

Author(s)	Disaster types	Phase	Input type	Supply capacity	Model objective	Main decisions	Time period	Solution method(s)
Drezner (2004)	General	Preparedness	Static	Un-capacitated	Covering, *P*-median, *P*-centre	Location	Single	Exact
Drezner *et al.* (2006)	General	Preparedness	Static	Un-capacitated	Covering, *P*-median, *P*-centre	Location	Single	Approximate
Edrissi *et al.* (2013)	Sudden, difficult	Mitigation, preparedness, response	Stochastic	Un-capacitated	*P*-median	Location, relief distribution	Single	Approximate
Galindo and Batta (2013)	Sudden, easy	Preparedness	Stochastic	Capacitated	*P*-median	Location, relief distribution	Single	Approximate
Hu *et al.* (2012)	Sudden, difficult	Preparedness	Static	Capacitated	Covering	Location	Single	Approximate
Huang *et al.* (2010)	General	Response	Static	Un-capacitated	*P*-centre	Location	Single	Approximate
Jia *et al.* (2007a)	General	Preparedness, response	Stochastic	Un-capacitated	Covering, *P*-median, *P*-centre	Location	Single	Exact
Jia *et al.* (2007b)	Sudden	Preparedness	Stochastic	Un-capacitated	Covering	Location	Single	Approximate
Jing *et al.* (2010)	General	Preparedness	Stochastic	Capacitated	*P*-median	Location, relief distribution	Single	Approximate
Kandel *et al.* (2011)	General	Preparedness	Static	Un-capacitated	*P*-median	Location	Single	Approximate
Kongsomsaksakul *et al.* (2005)	Sudden, easy	Preparedness	Static	Capacitated	*P*-median	Location, victim transportation	Single	Approximate
Kulshrestha *et al.* (2011)	General	Preparedness	Stochastic	Capacitated	*P*-median	Location, victim transportation	Single	Approximate
Kusumastuti *et al.* (2013)	General	Response	Static, dynamic	Capacitated, un-capacitated	Covering, *P*-median	Location, relief distribution	Single, multi	Exact
Lee *et al.* (2009a)	General	Preparedness	Static	Capacitated	Covering, *P*-median	Location, capacity	Single	Approximate
Lee *et al.* (2009b)	General	Preparedness	Static	Capacitated	Covering, *P*-median	Location, capacity	Single	Approximate
Li and Jin (2010)	Sudden, easy	Preparedness, response	Stochastic	Capacitated	*P*-median	Location, capacity, inventory, victim transfer	Single	Approximate

Table 2.3 Research on disaster-related LAPs ... (continued)

Author(s)	Disaster types	Phase	Input type	Supply capacity	Model objective	Main decisions	Time period	Solution method(s)
Li *et al.* (2011)	Sudden, difficult	Response	Stochastic	Capacitated	*P*-median	Location, relief distribution	Single	Approximate
Lodree *et al.* (2012)	Sudden, easy	Preparedness	Stochastic	Un-capacitated	*P*-median	Location, relief distribution	Single	Exact, approximate
Mahecha and Akhavan-Tabatabaei (2012)	Sudden, difficult	Preparedness	Static	Capacitated	*P*-median	Location	Single	Exact
Mete and Zabinsky (2010)	General	Preparedness, response	Stochastic	Capacitated	*P*-median	Location, inventory, routing	Single	Exact
Murali *et al.* (2012)	Sudden, difficult	Preparedness	Stochastic	Capacitated	*P*-median	Location	Single	Approximate
Park *et al.* (2012)	Sudden, difficult	Preparedness	Stochastic	Capacitated	Covering	Location	Single	Approximate
Paul and Hariharan (2012)	General	Preparedness, response	Stochastic	Capacitated	*P*-median	Location, capacity, victim transportation	Single	Exact
Paul and Batta (2008)	General	Preparedness	Static	Capacitated	Covering	Location, capacity	Single	Approximate
Ratick *et al.* (2008)	General	Preparedness	Static	Un-capacitated	Covering	Location	Single	Exact
Rawls and Turnquist (2010)	General	Preparedness, response	Stochastic	Capacitated	*P*-median	Location, inventory, relief distribution	Single	Approximate
Rawls and Turnquist (2011)	General	Preparedness, response	Stochastic	Capacitated	*P*-median	Location, inventory, relief distribution	Single	Exact
Rawls and Turnquist (2012)	General	Preparedness, response	Stochastic	Capacitated	*P*-median	Location, inventory, relief distribution	Multi	Exact
Rekik *et al.* (2013)	General	Response	Static	Un-capacitated	Covering	Location, relief distribution, vehicle routing	Single	Exact
Salmeron and Apte (2010)	Sudden, easy	Preparedness	Stochastic	Capacitated	*P*-median	Location, relief distribution, victim transportation	Single	Exact

Table 2.3 Research on disaster-related LAPs ... (continued)

Author(s)	Disaster types	Phase	Input type	Supply capacity	Model objective	Main decisions	Time period	Solution method(s)
Sherali *et al.* (1991)	Sudden, easy	Preparedness	Static	Capacitated	*P*-median	Location, victim transportation	Single	Approximate
Widener and Horner (2011)	Sudden, easy	Response	Static	Capacitated	*P*-median	Location	Single	Exact
Xiang-lin *et al.* (2010)	General	Preparedness	Stochastic	Un-capacitated	Covering	Location	Single	Approximate
Xiang-lin and Yun-xian (2009a)	General	Preparedness	Stochastic	Un-capacitated	Covering	Location	Single	Approximate
Xiang-lin and Yun-xian (2009b)	General	Preparedness	Stochastic	Un-capacitated	Covering	Location	Single	Approximate
Xue *et al.* (2012)	General	Preparedness	Static	Un-capacitated	*P*-median	Location	Single	Approximate
Yushimito *et al.* (2010)	General	Preparedness	Static	Un-capacitated	Covering	Location	Single	Approximate
Zhan and Liu (2011)	General	Preparedness	Stochastic	Un-capacitated	*P*-median	Location, relief distribution	Single	Exact
Zhang *et al.* (2013)	General	Preparedness	Static	Un-capacitated	*P*-median	Location	Single	Approximate
Zhu *et al.* (2010)	General	Preparedness	Static	Capacitated	*P*-median	Location	Single	Approximate

Kusumastuti *et al.* (2013)) are concerned with activities in the response stage of disaster management. Research papers such as An *et al.* (2013), Bozorgi-Amiri *et al.* (2013), Döyen *et al.* (2011), Jia *et al.* (2007a) and Rawls and Turnquist (2012), meanwhile, are devoted to activities in both the preparedness and response phases. Edrissi *et al.* (2013), finally, is concerned with activities in the mitigation, preparedness and response stages.

The papers are also categorised with regard to input characteristics of the data, i.e. static, dynamic, deterministic or stochastic in nature. Ablanedo-Rosas *et al.* (2009), Alcada-Almeida *et al.* (2009), Hu *et al.* (2012), Mahecha and Akhavan-Tabatabaei (2012) and Widener and Horner (2011), for example, deal with static input parameters. One of the two models in Kusumastuti *et al.* (2013), meanwhile, is concerned with dynamic input parameters. The majority of the research papers (such as An *et al.* (2013), Balcik and Beamon (2008), Bozorgi-Amiri *et al.* (2013), Chang *et al.* (2007), Döyen *et al.* (2011), Edrissi *et al.* (2013), Galindo and Batta (2013), Jia *et al.* (2007a), Jia *et al.* (2007b), Li *et al.* (2011), Rawls and Turnquist (2012) and Salmeron and Apte (2010)) address problems with stochastic input parameters.

Capacity of sites is another important aspect by which research papers may be classified. Alcada-Almeida *et al.* (2009), Balcik and Beamon (2008), Bozorgi-Amiri *et al.* (2013), Chang *et al.* (2007), Döyen *et al.* (2011), Galindo and Batta (2013), Li *et al.* (2011), Mahecha and Akhavan-Tabatabaei (2012), Rawls and Turnquist (2012) and Widener and Horner (2011), for example, relate to capacitated LAP. Research such as that by Ablanedo-Rosas *et al.* (2009), An *et al.* (2013), Edrissi *et al.* (2013), Jia *et al.* (2007a) and Jia *et al.* (2007b), in the meantime, deal with LAPs where there are no particular limits on site capacity.

Models on LAP can also be classified according to model objectives. In this respect, it seems that the majority of research papers under concern fall into *P*-median models (see, for instance, Alcada-Almeida *et al.* (2009), An *et al.* (2013), Döyen *et al.* (2011), Edrissi *et al.* (2013), Galindo and Batta (2013), Li *et al.* (2011), Mahecha and Akhavan-Tabatabaei (2012), Rawls and Turnquist (2012), Salmeron and Apte (2010)). Much research work such as Ablanedo-Rosas *et* *al.*(2009), Balcik and Beamon (2008), Jia *et al.* (2007b) and Yushimito *et al.* (2010) deals with covering problems. *P*-centre problems solely (as they appear in the objective function(s)) can be found in Huang *et al.* (2010) and in model I in Kusumastuti *et al.* (2013), and the use of *P*-centre approach along with either *P*-median or covering or both appears in work by Bozorgi-Amiri *et al.* (2013), Drezner (2004), Drezner *et al.* (2006) and Jia *et al.* (2007a), to name a few.

Location is the main decision in all of the research papers under review. The location aspect can be the only decision (see, for example, Ablanedo-Rosas *et al.* (2009), Drezner (2004), Drezner *et al.* (2006), Hu *et al.* (2012), Jia *et al.* (2007a) and Jia *et al.* (2007b), Mahecha and Akhavan-Tabatabaei (2012) and Widener and Horner (2011)) or in combination with other decision(s) such as inventory level (see, for instance, Balcik and Beamon (2008) and Campbell and Jones (2011)), relief distribution (e.g. Edrissi *et al.* (2013), Galindo and Batta (2013), Kusumastuti *et al.* (2013) and Li *et al.* (2011)), victim transportation (e.g. Alcada-Almeida *et al.* (2009), An *et al.* (2013), Chang *et al.* (2007) and Kongsomsaksakul *et al.* (2005)), inventory and relief distribution (e.g. Bozorgi-Amiri *et al.* (2013), Döyen *et al.* (2011) and Rawls and Turnquist (2012)), inventory and routing in sequential order such as that in Mete and Zabinsky (2010) or relief distribution and victim transportation such as that in Salmeron and Apte (2010).

With regard to time period, it is apparent that most of the research papers under review approach the problems statically. Only two research papers (i.e. Balcik and Beamon (2008) and Rawls and Turnquist (2012)) and one model (i.e. model II in Kusumastuti *et al.* (2013)) deal with the associated problem under concern dynamically.

Solution method(s) is the final criteria applied in the review. In this respect, either exact methods or approximate approaches come into play in roughly equal measure. Ablanedo-Rosas *et al.* (2009), Bozorgi-Amiri *et al.* (2013), Kusumastuti *et al.* (2013) and Salmeron and Apte (2010) are examples of research papers with exact methods as solution approaches. Approximate methods are employed by, for instance, Alcada-Almeida *et al.* (2009), Döyen *et al.* (2011) and Galindo and

Batta (2013). Few research papers (see, e.g., Doerner *et al.* (2009) and Lodree *et al.* (2012)) employ exact methods as well as approximate approaches.

From the summary, it should be mentioned that only Rawls and Turnquist (2012) and one of the model in Kusumastuti *et al.* (2013) deal with the optimisation of location selection and relief distribution dynamically. The latter, in particular, is concerned with the activities of positioning the temporary distribution centres and distributing the related relief commodities after a particular disaster occurrence. Salmeron and Apte (2010), in the meantime, deal with the optimisation of location positioning, relief distribution and casualty transportation. In contrast to one of the models in Kusumastuti *et al.* (2013), the three activities in Salmeron and Apte (2010) take place in the preparedness stage of disaster management. These three research papers are further reviewed and are presented in the following paragraphs.

Rawls and Turnquist (2012) take into account location to be pre-positioned, inventory level of emergency supplies in that location and quantity of the supplies to fulfil demands. Uncertainties regarding the demands and transportation network availability due to disaster events are reflected in particular scenarios. The researchers develop a two-stage stochastic mixed integer program (SMIP) to solve the problem. The research addresses the allocation part of the problem dynamically.

An optimisation of temporary facility positioning and relief distribution in response stage of disaster management is the main concern of Kusumastuti *et al.* (2013). The research deals with a four-layer relief logistics network, where distribution facilities at district level and village level need to be positioned and relief distribution from provincial level facilities through district level facilities to village level facilities need to be optimised. For that purpose, two different mathematical models are subsequently constructed. A static model – which is a slight modification of a maximal covering location problem – is built and aims to determine locations of village level distribution facilities within a given budget that maximises the expected number of casualties that can be served by the facilities during the overall period of disaster relief. The output from this model is fed into a dynamic model where locations of district level facilities and relief distribution from provincial level facilities to the district facilities are determined under a certain limited budget and aims to minimise the total delivery time of relief from the provincial level facilities to village level facilities. A real problem of a flood taking place in Jakarta Province is used to give evidence about the merit of the proposed models.

Salmeron and Apte (2010) deal with the problem of capacity expansion (including the possibility of having new sites), relief distribution, and victim transportation. The authors approach the problem statically. In the paper, resources already exist or can be prepositioned in relief locations. Victims, meanwhile, are classified into three different categories: (1) critical victims needing to be evacuated to relief locations for medical treatment, (2) stay-back victims who may stay in affected areas but need to be supplied with relief from relief locations, and (3) transfer victims who need to be evacuated to relief locations due to their temporary displacement status. To minimise the expected number of casualties under a variety of disaster scenarios, the authors develop a two-stage stochastic optimisation model. The first stage of the model is concerned with the decision on expansion of resources. Vehicles needed, relief delivered to those in need and victims transported to related sites, in the meantime, are the main concern of the second stage of the model.

2.8.4 Location-Routing Problems (LRPs)

Location aspects are also found in the location-routing problem category. The same issues applied in the review of LAPs above (i.e. disaster types, disaster management phase, types of input parameters, capacity of the sites, objective(s) in the related mathematical model(s), main decisions found in the research, time period of the research and solution method(s) utilised in the research) are also employed in the LRP category within disaster logistic optimisation for the reason that the main focus of LRP is on location aspects. The categorisation process is preceded by a brief presentation on LRPs.

Given a set of candidate depot sites and customer requirements, LRP in its simplest form can be seen as comprising the determination of the depots' location and the routes of the vehicles devoted to serve the customers, in such a way that constraints, which generally relate to the capacity of depots and vehicles, length and duration of routes, and the requirements stemming from customers, are met and, at the same time, an objective function which usually incorporates routing costs, vehicle fixed costs, depot fixed costs and depot operating costs, is minimized (Ambrosino and Grazia Scutellà, 2005). Regarding this definition, it is reasonable to conclude that LRP addresses several aspects of a distribution network design problem (Ambrosino and Grazia Scutellà, 2005).

The location-routing problem can be seen as a certain type of location analysis (Nagy and Salhi, 2007). It addresses facility location and vehicle routing aspects simultaneously (Ambrosino *et al.*, 2009). In contrast to the location-allocation problem which assumes a straight-line or radial journey from the supply centres to the customer locations (Min *et al.*, 1998), LRP necessitates the tours in the journey process from the depot's location to the customers' sites (Min *et al.*, 1998). A review of LRP can be found in Min *et al.* (1998) and Nagy and Salhi (2007).

Unlike LAPs, research on LRP within disaster logistic optimisation is not so plentiful. Included in this category of disaster logistic optimisation are those performed by Yi and Özdamar (2007), Ukkusuri and Yushimito (2008), Han *et al.* (2007, 2010, 2011), Afshar and Haghani (2012), Lin *et al.* (2012), Rath and Gutjahr (2014) and Abounacer *et al.* (2014).

Some of the research deals with disasters in general (see, for instance, Yi and Özdamar (2007), Afshar and Haghani (2012), Abounacer *et al.* (2014) and Rath and Gutjahr (2014)), and one paper (Lin *et al.* (2012)) addresses particular types of disaster. Most of the research (e.g. Yi and Özdamar (2007), Han *et al.* (2011), Lin *et al.* (2012), Afshar and Haghani (2012), Rath and Gutjahr (2014) and Abounacer *et al.* (2014)) is devoted to the response phase of the disaster cycle, and only one paper (Ukkusuri and Yushimito, 2008) is concerned with site positioning at the preparedness stage. Several research works treat the input parameters as constant (see, for example Abounacer *et al.* (2014) and Rath and Gutjahr (2014)), whereas the others handle the inputs dynamically (see Yi and Özdamar (2007), Han *et al.* (2010), Han *et al.* (2011), Lin *et al.* (2012) and Afshar and Haghani (2012), for instance). For the reason of the dynamic nature of input parameters, some authors propose to address the problem under concern dynamically (e.g. Yi and Özdamar (2007), Han *et al.* (2011), Lin *et al.* (2012) and Afshar and Haghani (2012)). Most authors solely use a *P*-median model in the objective function(s) (see, e.g., Yi and Özdamar (2007), Han *et al.* (2011), Lin *et al.* (2012), Abounacer *et al.* (2014), Rath and Gutjahr (2014) and Afshar and Haghani (2012)). Several authors (e.g. Yi and Özdamar (2007) and Afshar and Haghani (2012)) handle the location aspect of the problem dynamically. Table 2.4 gives a summary of the papers under review.

Table 2.4 Research on disaster-related LRPs

Author(s)	Disaster types	Phase	Input type	Supply capacity	Model objective	Main decisions	Time period	Solution method(s)
Abounacer *et al.* (2014)	General	Response	Static	Capacitated	*P*-median	Location, relief distribution and vehicle routing	Single	Exact, approximate
Afshar and Haghani (2012)	General	Response	Dynamic	Capacitated	*P*-median	Location, relief distribution and vehicle routing	Multi	Approximate
Han *et al.* (2007)	General	Response	Dynamic	Un-capacitated	*P*-median	Location, vehicle routing	Multi	Exact
Han *et al.* (2010)	General	Response	Dynamic	Un-capacitated	*P*-median	Location, vehicle routing	Multi	Approximate
Han *et al.* (2011)	General	Response	Dynamic	Un-capacitated	*P*-median	Location, vehicle routing	Multi	Approximate
Lin *et al.* (2012)	Sudden, difficult	Response	Dynamic	Capacitated	*P*-median	Location, relief distribution and vehicle routing	Multi	Approximate
Rachaniotis *et al.* (2013)	General	Response	Static, stochastic	Un-capacitated	Covering, *P*-median	Location, relief distribution, vehicle routing	Single, multi	-
Rath and Gutjahr (2014)	General	Response	Static	Capacitated	*P*-median	Location, relief distribution and vehicle routing	Single	Approximate
Ukkusuri and Yushimito (2008)	General	Preparedness	Static	Un-capacitated	Covering	Location, routing	Single	Exact
Yi and Özdamar (2007)	General	Response	Dynamic	Capacitated	*P*-median	Location, relief distribution, victim transportation and vehicle routing	Multi	Approximate

To the best knowledge of the researcher, the simultaneous optimisation of site positioning, relief distribution and victim transportation in dynamic environment is only found in Yi and Özdamar (2007). The paper is outlined below, for the reason of its relevance to the present research.

Commodity dispatch, evacuation and transfer of injured people to emergency units, selection of locations for temporary emergency centres and shelters in the affected regions, and an optimal medical personnel allocation on both temporary and permanent emergency units in nearby hospitals might take place simultaneously in logistics planning in disaster response activities. To overcome this type of problem, Yi and Özdamar (2007) develop a two-stage mixed integer multi-commodity network flow model. This model treats vehicles as integer commodity flows rather than binary variables in the first stage. In the second stage, a vehicle splitting algorithm that converts integer vehicle flows into binary vehicle routes is employed at first. Subsequently a set of linear equations is solved to assign a loading/ unloading schedule to each such journey. At the end of the second stage, detailed vehicle instructions are obtained. In the paper, the proposed procedure is then compared with the VRP based single-stage model built for the same problem. The proposed model is shown to be superior with respect to model size, number of binary/ integer variables, number of constraints, computation time and iteration count.

2.9 Facility Deployment in Disaster Context

With respect to relief distribution and victim transportation, location of facilities (and allocation of ‘customers’ to the facilities) is closely related to facility deployment strategies. As noted by Jia *et al.* (2007a), facility deployment strategies in response to large-scale disaster occurrences can be categorised into proactive and reactive facility deployment. Slow-onset disasters usually have delayed effects and yet need continuous and large amounts of relief supplies. In response to this type of disaster, a reactive strategy is hence more appropriate. Sudden-onset disaster arrivals, on the other hand, need supplies to be kept in particular facilities prior to disaster onset. In other words, this type of disaster is better approached by a proactive facility deployment strategy. This will enable a quick delivery of commodity supplies to demand points.

It is generally recognizable that, following the occurrence of a particular disaster with large impact and which is difficult to predict, necessary on-site facilities are broken or their service capacities decreased (see, for instance, Huang *et al.* (2010)). In order to give the best service, hence, there is a common need to provide backup to the facilities with decreasing service capacities and, to some degree, to restoring those aforementioned facilities using those from other areas. Assistance from other regions comes to the disaster areas even in the situation where the facilities on site remain in full service, as a particular event declared as a disaster simply means that the current capacity of the affected societies cannot cope with the disaster impact. All of these incoming facilities need to be positioned.

The research papers with location aspects – i.e. those presented in Sub-sections 2.8.3 and 2.8.4- can be re-examined with reference to facility deployment strategies as they are defined in Jia *et al.* (2007a) above, disaster types and whether the location aspects are simultaneously handled along with vehicle routing aspects (if any). Table 2.5 summarises this re-examination.

Table 2.5 Re-examination of research papers containing location positioning

Author(s)	Disaster types	Facility deployment strategies	Vehicle routing aspects	
			Yes or no	If any, dealt simultaneously or not
Ablanedo-Rosas *et al.* (2009)	General	Proactive	No	
Abounacer *et al.* (2014)	General	Reactive	Yes	Yes
Afshar and Haghani (2012)	General	Reactive	Yes	Yes
Alcada-Almeida *et al.* (2009)	General	Proactive	No	
An *et al.* (2013)	Sudden	Proactive	No	
Balcik and Beamon (2008)	Sudden	Proactive	No	
Bozorgi-Amiri *et al.* (2013)	General	Proactive	No	
Bozorgi-Amiri *et al.* (2012)	General	Proactive	No	
Campbell and Jones (2011)	General	Proactive	No	
Chang *et al.* (2007)	Sudden, easy	Proactive	No	
Chi *et al.* (2011)	General	Proactive	No	
Chowdhury *et al.* (1998)	Sudden	Proactive	No	
Dekle *et al.* (2005)	General	Reactive	No	
Doerner *et al.* (2009)	Sudden, difficult	Proactive	No	
Döyen *et al.* (2011)	Sudden, difficult	Proactive	No	
Drezner (2004)	General	Proactive	No	
Drezner *et al.* (2006)	General	Proactive	No	
Edrissi *et al.* (2013)	Sudden, difficult	Proactive	No	
Galindo and Batta (2013)	Sudden, easy	Proactive	No	
Han *et al.* (2007)	General	Reactive	Yes	Yes
Han *et al.* (2010)	General	Reactive	Yes	Yes
Han *et al.* (2011)	General	Reactive	Yes	Yes

Table 2.5 Re-examination of ... (continued)

Author(s)	Disaster types	Facility deployment strategies	Vehicle routing aspects	
			Yes or no	If any, dealt simultaneously or not
Hu *et al.* (2012)	Sudden, difficult	Proactive	No	
Huang *et al.* (2010)	General	Reactive	No	
Jia *et al.* (2007a)	General	Proactive	No	
Jia *et al.* (2007b)	Sudden	Proactive	No	
Jing *et al.* (2010)	General	Proactive	No	
Kandel *et al.* (2011)	General	Proactive	No	
Kongsomsaksakul *et al.* (2005)	Sudden, easy	Proactive	No	
Kulshrestha *et al.* (2011)	General	Proactive	No	
Kusumastuti *et al.* (2013)	General	Reactive	No	
Lee *et al.* (2009a)	General	Proactive	No	
Lee *et al.* (2009b)	General	Proactive	No	
Li and Jin (2010)	Sudden, easy	Proactive	No	
Li *et al.* (2011)	Sudden, difficult	Reactive	No	
Lin *et al.* (2012)	Sudden, difficult	Reactive	Yes	Yes
Lodree *et al.* (2012)	Sudden, easy	Proactive	No	
Mahecha and Akhavan-Tabatabaei (2012)	Sudden, difficult	Proactive	No	
Mete and Zabinsky (2010)	General	Proactive	Yes	No
Murali *et al.* (2012)	Sudden, difficult	Proactive	No	
Park *et al.* (2012)	Sudden, difficult	Proactive	No	
Paul and Hariharan (2012)	General	Proactive	No	
Paul and Batta (2008)	General	Proactive	No	
Rachaniotis *et al.* (2013)	General	Reactive	Yes	Yes

Table 2.5 Re-examination of ... (continued)

Author(s)	Disaster types	Facility deployment strategies	Vehicle routing aspects	
			Yes or no	If any, dealt simultaneously or not
Rath and Gutjahr (2014)	General	Reactive	Yes	Yes
Ratick *et al.* (2008)	General	Proactive	No	
Rawls and Turnquist (2010)	General	Proactive	No	
Rawls and Turnquist (2011)	General	Proactive	No	
Rawls and Turnquist (2012)	General	Proactive	No	
Rekik *et al.* (2013)	General	Reactive	Yes	No
Salmeron and Apte (2010)	Sudden, easy	Proactive	No	
Sherali *et al.* (1991)	Sudden, easy	Proactive	No	
Ukkusuri and Yushimito (2008)	General	Proactive	Yes	Yes
Widener and Horner (2011)	Sudden, easy	Reactive	No	
Xiang-lin *et al.* (2010)	General	Proactive	No	
Xiang-lin and Yun-xian (2009a)	General	Proactive	No	
Xiang-lin and Yun-xian (2009b)	General	Proactive	No	
Xue *et al.* (2012)	General	Proactive	No	
Yi and Özdamar (2007)	General	Reactive	Yes	Yes
Yushimito *et al.* (2010)	General	Proactive	No	
Zhan and Liu (2011)	General	Proactive	No	
Zhang *et al.* (2013)	General	Proactive	No	
Zhu *et al.* (2010)	General	Proactive	No	

It is concluded that most research papers without simultaneous optimisation of vehicle routing – including those which deal with sudden-onset disasters – employ a proactive strategy in determining the location of sites under concern and this positioning decision, therefore, takes place in the preparedness phase of disaster management. Most of the research papers that are concerned with site positioning after the occurrence of disasters, in the meantime, are those with routing of vehicles handled concurrently with location positioning.

The majority of research papers with a reactive facility deployment strategy (see Abounacer *et al.* (2014), Afshar and Haghani (2012), Dekle *et al.* (2005), Han *et al.* (2007), Han *et al.* (2010), Han *et al.* (2011), Kusumastuti *et al.* (2013), Li *et al.* (2011), Lin *et al.* (2012), Rachaniotis *et al.* (2013), Rath and Gutjahr (2014), Rekik *et al.* (2013), Widener and Horner (2011) and Yi and Özdamar (2007)) are concerned with facilities that are located temporarily. The temporary facilities are expected to provide services mostly during the planning horizon of disaster management, where Yi and Özdamar (2007) and Afshar and Haghani (2012) locate the temporary facilities during the planning horizon dynamically. Permanent facility positioning, in the meantime, is only found in Huang *et al.* (2010). Among the papers of which site positioning is performed after the disaster occurrence, Li *et al.* (2011) and Lin *et al.* (2012) specifically address sudden-onset, difficult-to-predict natural disasters.

2.10 Research Significance

The research problem and its background have already been formulated and are provided in Chapter 1. The literature relevant to the research problem forms the earlier part of this chapter. This section provides the connection between the current research and previous work and, ultimately, provides an explanation about the position and hence contribution, of the current research.

2.10.1 Identified Problem and Its Association with Previous Work

By concurrently considering the research problem (see Chapter 1) and the reviewed literature (see previous parts of this chapter), it can be stated that the research problem under concern can be seen as an LAP-type problem. With regard to the facility aspects contained in the current research problem, it is also evident that it is relatively close to an LRP-type problem. In general, LAP deals with the problem of locating facilities and allocating demand points/ areas to these facility locations. The inclusion of vehicle route selection along with the facility positioning, in the meantime, distinguishes LRP-type problems from LAPs.

Relating to the research addressed in the thesis, temporary facilities under concern consist of: (1) temporary intermediate distribution points – from which commodities are distributed, and (2) temporary medical centres/ facilities – which provide services to the injured victims. Fixed locations included in the current research, meanwhile, are existing medical facilities (i.e. the facilities which also give service to the injured victims) and disaster areas (i.e. the areas from which the victims come).

The inclusion of relief distribution and casualty transportation in site location is found in Salmeron and Apte (2010). Dynamic ways of sending relief and/ or transporting victims are chosen by Kusumastuti *et al.* (2013), Rawls and Turnquist (2012), Afshar and Haghani (2012), Han *et al.* (2007), Han *et al.* (2010), Han *et al.* (2011), Lin *et al.* (2012), Rachaniotis *et al.* (2013) and Yi and Özdamar (2007). The need to establish temporary site locations in the response phase of the disaster management cycle has been researched by Abounacer *et al.* (2014), Afshar and Haghani (2012), Dekle *et al.* (2005), Han *et al.* (2007), Han *et al.* (2010), Han *et al.* (2011), Kusumastuti *et al.* (2013), Li *et al.* (2011), Lin *et al.* (2012), Rachaniotis *et al.* (2013), Rath and Gutjahr (2014), Rekik *et al.* (2013), Widener and Horner (2011) and Yi and Özdamar (2007).

2.10.2 Unique Features of the Current Research

As discussed in the literature review, the optimal site location of temporary facilities following a disaster has already been addressed by several researchers. The inclusion of relief distribution attributes and victim transportation aspects together with a dynamic approach to optimisation, on the other hand, has not been widely addressed. To the best knowledge of the researcher, only Yi and Özdamar

(2007) have considered the simultaneous dynamic optimisation of the determination of temporary emergency centres, the distribution practice of disaster relief and the evacuation process of the injured victims after natural disaster occurrences.

It is generally accepted, however, that location-related decisions (in this case, the number and locations of temporary facilities) are strategic issues, whereas commodity dispatch and routing (in this case, relief distribution and victim evacuation process routing) are operational issues. Therefore, instead of treating facility location, commodity dispatch, and evacuation process routing simultaneously, it is more practical to treat them in stages: determining the facility location first and then making the detailed vehicle routing decisions for commodity distribution and victim evacuation with the fixed facility locations.

This research focuses on the first stage, i.e. facility location (and allocation) in the response phase of disaster management. More specifically, it pays attention to the location-allocation aspects of last-mile relief distribution and victim evacuation following a sudden-onset, difficult-to-predict natural disaster. In this respect, the current research is related to previous work on location-allocation problems in disaster management.

An additional difference between the current research and that by Yi and Özdamar (2007) lies in how the temporary facilities are treated. This difference is elaborated below.

The work by Yi and Özdamar (2007) implicitly deals with location aspects by allocating optimal service rates to existing medical centres and temporary emergency centres according to which patients are freed from the system. In the sense of temporary emergency centres, they utilize the medical resources of hospitals/ medical centres in the area and consume some of the total health care capacity in that locale.

The on-going research, on the other hand, concentrates on the location decisions for temporary sites – consisting of temporary intermediate distribution points and temporary medical facilities – rather than for temporary emergency centres solely. After being selected, these temporary sites remain present for the remainder of the planning horizon. Also different from Yi and Özdamar (2007), temporary medical facilities that are included in this research carry out the same function as those of existing medical facilities. Finally, these temporary medical facilities will not consume some of the total capacity of the existing medical facilities. Instead, these temporary medical facilities come from other unaffected areas, e.g. in the form of temporary field hospitals (see, for instance, Memarzadeh *et al.* (2004) and Loghmani *et al.* (2008) on the establishment of field hospitals).

The inclusion of additional resources such as incoming medical facilities from other areas will give the authority larger capability in dealing with the relief distribution and victim evacuation. The decision about distribution centre locations gives the authority greater flexibility in responding to the disaster event. The established temporary sites, which remain present for the remainder of the planning horizon, are easier to manage. These three features (i.e. greater capability, flexibility and simplicity) as well as the practical characteristics provide advantages to the current approach in comparison with that proposed by Yi and Özdamar (2007).

CHAPTER 3
MATHEMATICAL MODELS

This chapter presents all mathematical models developed to represent different approaches to the problem under study. The mathematical models are presented with the related specific assumptions. Prior to this, the general settings for the models and common assumptions applicable to all the models are first described.

3.1 General Settings

Natural disasters are highly likely to lead to severe problems, including extensive human misery and property losses or damage. It is therefore vital to respond quickly to natural disasters – especially sudden-onset natural disasters. The response includes the positioning of temporary facilities for last-mile relief distribution and for victim evacuation and medical treatment.

Location of facilities can be proactive or reactive. The reactive strategy is appropriate for slow-onset disasters which usually have delayed effects and yet need continuous and large amount of relief supplies. Sudden-onset disasters, on the other hand, need instantaneous response requiring supplies to be kept in particular facilities prior to the disaster arrivals.

The proactive approach is exactly what the Ministry of Social Affairs and the Ministry of Health, the Republic of Indonesia, take in anticipation of disaster arrivals (Kusumastuti *et al.* (2013); interview by the researcher). The Ministry of Social Affairs has already built a certain number of warehouses at various levels of the disaster logistical chain (i.e. at national and provincial level and some at district/ municipality levels), whereas the Ministry of Health has already set up some Centres for Disaster Management. In addition, in each district/municipality, there is usually a warehouse for medical-related goods (e.g. drugs, medicine). From these facility locations, commodity supplies as well as medical teams are dispatched to disaster areas, when a disaster strikes. There are also hospitals and other medical facilities, serving as the destinations of injured victims in the disaster areas.

Despite the existence of the abovementioned locations, new locations (and allocation of demand points to them) still need to be established soon after a disaster event (i.e. at the final stage of the disaster logistical chain). This means that the reactive deployment strategy is also needed.

The necessity for determining new locations and allocating the demand points to both types of locations (i.e. existing and new) stems from at least three sources. First, existing facilities may have been incapacitated due to the disaster event. Therefore, new facilities have to be set up. Second, the disasters may take place in such a way that existing and functioning facilities (if any) cannot provide service optimally. Third, commodity relief and medical teams coming from outside in response to a particular disaster need to be situated in appropriate locations.

Disaster logistics at the final stage of the disaster logistical chain is generally called last-mile logistical operation systems (Balcik *et al.* (2008); Özdamar and Demir (2012)). It is stated by Beamon (2004) that last mile relief distribution network configuration is one of the challenging issues in relief chain management.

The research in this thesis is enriched by a field study on disaster management in Indonesia. More specifically, the West Sumatera earthquake that took place on 30 September 2009 is used as a base for mathematical model building.

Despite the existence of an Implementing Unit for Disaster Management in Padang Pariaman District, the distribution of relief and the evacuation of injured victims were carried out by different governmental agencies. The commodity relief distribution to sub-districts was performed by the Ministry of Social Affairs agency in the district. In each sub-district, the local government body was in charge of the relief distribution. The locations for temporary distribution supplies in the sub-district were also decided by the same government body. The Ministry of Health agency in the district, on the other hand, carried out the injured victim evacuation. The allocation of incoming medical facilities to particular areas was also conducted by this agency. Each of the in-charge governmental agencies was also responsible in providing vehicles for the relief distribution or the injured victim evacuation and, as a consequence, the vehicles available for the relief distribution are different from those for the victim evacuation. All these activities were reported in a regular joint meeting coordinated by the Implementing Unit for Disaster Management and attended by all related agencies.

Based on the practice in Padang Pariaman District, disaster management is carried out in three levels. For model purposes and for consistency, we will use the following terms. The whole district affected by the disaster will be referred to as the *region* which is divided into *sub-regions*. Each sub-region consists of a number of *disaster areas*. Each disaster area is a basic unit which will not be further divided. This significantly reduces model complexity and hence model size and associated solution time. Figure 3.1 shows a schematic example of the region, sub-regions and disaster areas.

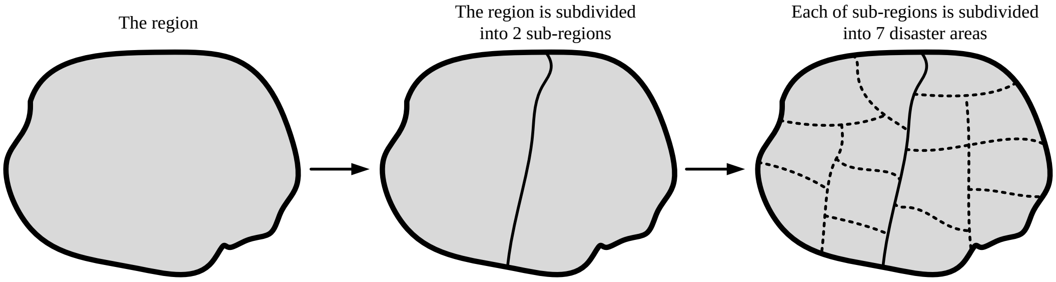


Figure 3.1 A schematic example of region, sub-regions and disaster areas

Interviews conducted by the researcher reveal a policy for commodity relief distribution which is to send the amounts of commodities to disaster areas ideally in proportion to the estimated numbers of lives in the areas.

The deployment of incoming medical facilities to areas is performed by using the following criteria, in order of priority: (1) To cover disaster areas according to their level of severity, (2) To cover any areas without medical facility coverage (because existing medical facilities are affected by the disaster, for instance), (3) (In case criteria 1 and 2 have already been met) To give support to existing medical facilities.

In order to reflect the situation in Padang Pariaman District after the West Sumatera earthquake, a ‘current-practice’ location allocation model is built which will be referred to as model I. It tries to represent, in many ways, the commodity relief distribution and victim evacuation practice that took place in the district. The model mainly consists of two parts. Sub-model Ia is devoted to the commodity relief distribution, whereas the victim evacuation process is represented by sub-model Ib. In line with the practice policy, the model tries to minimize the victim suffering in the worst area. Hence, both sub-models are of *P*-centre type. Minimizing the total suffering over all areas is also considered as a secondary objective. Thus, the model has a *P*-median feature as well.

It is frequently found that a national board for disaster management exists in a particular disaster context. In general, the existence of a command body – with sufficient power to instruct and coordinate – should permit more synchronic and coordinative decisions. Good coordination is proven to be able to minimise losses caused by disaster occurrences (Prizzia (2008); Balcik *et al.* (2010)). With respect to the response phase of disaster management, poor coordination is seen as one source, among others, of failure in the response (Thévenaz and Resodihardjo, 2010). Concerning Indonesia, the need to improve coordination during its disaster relief operations is supported by a research finding (van Rossum and Krukkert, 2010).

In Indonesia, a National Board for Disaster Management has already been set up. Its derivatives in several provinces and municipalities/districts have also already been established. The body and its derivatives have a command authority during the response phase after a disaster. It coordinates various agencies, either governmental or non-governmental organisations, involved in the response phase of disaster management.

In future, all provinces in Indonesia are obliged to have such a derivative body. Municipalities and/or districts, on the other hand, can choose whether to establish a derivative body. In case a particular municipality or district decides not to establish the body, the disaster management function is carried out by a particular organisation with disaster management capability.

It is also apparent that the arrival times of additional resources from other regions can be obtained in advance by the associated authorities in the disaster location. This is what exactly occurred in the aftermath of the West Sumatera earthquake (based on the interview performed by the researcher). The authorities of the Ministry of Health at central level, for example, let the authorities of the Ministry of Health at provincial and district levels know about their plan to send medical teams to the disaster region beforehand. This simply means that, in many circumstances, information about future resource availability can be acquired in advance with relatively high accuracy.

To fully utilise the coordinating agencies' coordination potential and/or the information on future resource availability, three further models are constructed. Model II is mainly characterised by allowing the commodity distribution and the victim evacuation to be carried out by the same vehicles. The inclusion of future resource availability information is the unique feature that differentiates model III from model I. Model IV accommodates both of these features. In other words, model IV is characterized by the following features: (1) Future information with respect to resource availability is included, and (2) It enables victim evacuation and commodity relief distribution to be jointly carried out. Model I described earlier will be used as a baseline for assessing the performance of all the models.

Graphically, the relationship amongst these four models is provided in Figure 3.2.

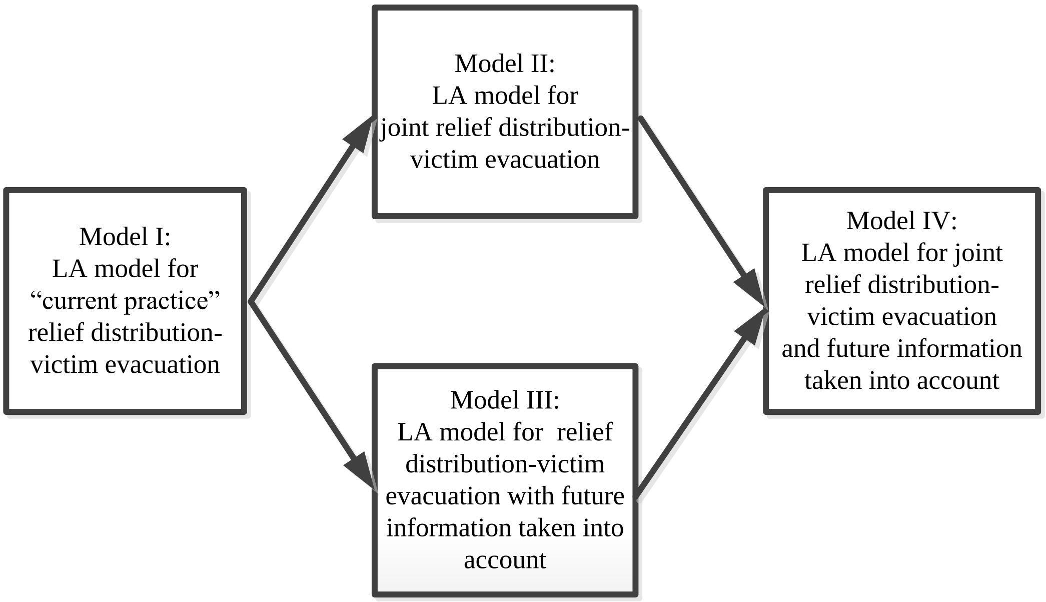


Figure 3.2 Relationship amongst the models

Model II, model III and model IV are expected to perform better than model I. It is also expected that, after a series of computational experiments and analysis and discussion, a clear insight about the benefits of combining the relief distribution and victim transportation or including future information about resource availability or having both can be obtained.

All four models take vehicle availability into consideration. According to the practice of the relevant agencies during the management of the 2009 West Sumatera earthquake, it is possible that incoming vehicles as well as incoming medical facilities leave the scene within the planning horizon. This is accommodated in the proposed models.

All the models run in a rolling horizon fashion. That is, the model is run (or implemented as we will sometimes call it later) immediately after the disaster with available and known resources, facilities and vehicles at that time to decide the locations of temporary medical centres and temporary commodity relief distribution centres, the allocation of the disaster areas and vehicles to these centres.

At the beginning of the next period (e.g. one day) or when new resources or information on future resource availability become available, the model is run/implemented again, considering the situation at the time. Temporary facilities set in previous periods are treated as existing ones in the subsequent model implementations.

In each run, the planning horizon of the model is from that time point to the end of the disaster relief effort when all injured victims are evacuated and sufficient commodity relief is distributed to all disaster areas. The operation will follow the decisions resulting from the model until the next run of the model which will plan and modify the decisions for the operations in the remaining periods.

The objective of the models is to minimize the suffering of the victims. This is represented by the number of un-evacuated injured victims multiplied by the duration of their waiting for evacuation as well as the unsatisfied relief demand (i.e. shortages) of the victims in the disaster areas multiplied by the duration over which demand is not met. While suffering exists in any disaster areas, we try to minimize suffering in the worst area as well as to minimize total suffering in all areas.

3.2 General Assumptions

General assumptions applied to all the models are provided in the following paragraphs.

A disaster may cause many victims. The research represents the area locations of victims as points. Moreover, these locations are assumed to be known.

The victims are categorised into two different classes: (1) Injured victims, and (2) Injury-free sufferers. Injured victims are treated individually and need to be evacuated for medical treatment. Injury-free sufferers, on the other hand, are assumed to stay in the disaster areas and need commodity relief delivered to them.

The injured victims in any disaster area have to be evacuated to a particular site with a medical facility. Similarly, the injury-free victims in the area have to be supplied by a particular site with a distribution centre for supplying commodity relief. In order to do so, at least one site with a distribution centre and one site with a medical facility are assumed to be available in every time period within the planning horizon.

In order to be able to send the required commodities, a number of temporary sites with distribution centres need to be open in each sub-region (for model I) or in the region (for models II, III and IV). They are decided once by local government in each sub-region (for model I) or by the government in the region (for models II, III and IV) at the beginning of the disaster relief operation. All candidate sites for the temporary distribution centres are assumed to be known.

In response to the disaster, medical teams from other regions or other countries arrive over time. They need, therefore, to be placed in particular sites. Along with existing sites with medical facilities which are still able to provide medical treatment, they function as the destinations of injured victim evacuation in the region. Locations of the candidate sites for temporary medical facilities as well as existing sites with medical facilities are assumed to be known.

In certain circumstances of disaster arrivals, the injury-free sufferers have to be evacuated/ relocated, far enough from the disaster areas. However, the research assumes that this activity is performed at the recovery-reconstruction phase. As a consequence, this activity is excluded from the study.

Travel times between locations are assumed to be known. These travel times already encompass additional times needed due to road damage, congestion, etc.

Transfer of injured victims from any medical facility to other medical facilities, if any, is not included in the models. Similarly, transportation of commodity relief from any distribution centre to other distribution centres, if any, is also excluded from the models. These two types of transportation, if they exist, are assumed to be performed by vehicles different from those used for victim evacuation and relief distribution.

Vehicles either for commodity relief distribution or for victim evacuation or for both activities are assumed to use particular sites as bases.

All vehicles available at sites at the beginning of the planning horizon are assumed ready to be allocated to any site. They are included in “vehicles available at time point 0”. As a consequence, all sites are assumed to have no vehicle at time point 0 of the first implementation of the model.

All vehicles are assumed to have the same capacity. This is because vehicles in last-mile commodity relief distribution and victim evacuation phase are very similar in size.

Both incoming medical facilities and incoming vehicles will not leave the disaster scene at the time as they arrive. This is because if they do so, then they will not make any contribution and so need not to be considered as part of the problem under study. As a consequence, there are no leaving vehicles at time point 0 of the first implementation of any of the four models.

Once a vehicle is allocated to a site at the beginning of a time period, it will serve the site during the whole of that period. Its movement to other sites is only possible at the beginning of the next period.

A penalty with the same value will be given for each un-evacuated injured victim in each period. A penalty with another constant value will also be given for each unit of unmet type-2-commodity relief demands in each period.

It is quite common that, following a disaster occurrence, a huge amount of commodity relief arrives at the disaster region/country. With respect to this situation, it is assumed that supplies of any commodities are unlimited.

3.3 Model I

As already mentioned, model I (the ‘current-practice’ location-allocation model) consists of two sub-models. Sub-model Ia reflects the practice of commodity relief distribution in Padang Pariaman District after the earthquake. Meanwhile, the practice of victim evacuation in the district is represented by sub-model Ib. All general assumptions are applicable to the model.

3.3.1 Additional Assumptions of Model I

Along with general assumptions previously presented, what follow are additional assumptions of model I.

Following the division of the region into sub-regions, each sub-region has a specific task to serve the commodity relief demands within the sub-region. As a consequence, the distribution sites in a particular sub-region only serve the commodity relief demands in the sub-region. The distribution activity is conducted by local government in the sub-region. Likewise, vehicles available for distribution purpose in a particular sub-region have to serve disaster areas in the sub-region only.

The division of the region into sub-regions does not affect the victim evacuation process. The evacuation of injured victims in any sub-region to any medical facility within the whole region is, therefore, allowed. The evacuation activity is conducted by the Ministry of Health agency in the region and its derivatives. Similarly, vehicles provided for evacuating injured victims are able to serve the injured victims in any sub-region.

Model I is run repeatedly every time new information arises. Outputs resulting from the implementation of the model in the first run will be used as inputs for the second run and so forth. Sub-model Ia is for individual sub-regions, whereas sub-model Ib is intended for the region as a whole.

3.3.2 Sets Used in Model I

Sets used in mathematical model I are as follows. As it can be seen later, some of these sets are also used in model III and/or model II and/or model IV.

R	Set of sub-regions, $R = \{1,2,\ldots,n_r\}$;
A^r	Set of disaster areas in sub-region $r \in R$, $\bigcap_{r\in R} A^r = \emptyset$;
A	Set of all disaster areas, $A = \bigcup_{r\in R} A^r$;
$\mathcal{D}_o^r$	Set of existing sites with distribution centres but not allowed to have medical facilities in sub-region $r \in \mathcal{R}$, $\bigcap_{r\in R} \mathcal{D}_o^r = \emptyset$;
$\mathcal{M}_o$	Set of existing sites with medical facilities but not allowed to have distribution centres;
$\mathcal{P}_d^r$	Set of candidate sites for temporary distribution centres in sub-region $r \in R$, $\bigcap_{r\in R} \mathcal{P}_d^r = \emptyset$;
$\mathcal{P}_m$	Set of candidate sites for temporary medical facilities;
α_d^r	Set of all sites either with existing distribution centres or candidates for distribution centres in sub-region r,$\alpha_d^r = \mathcal{D}_o^r \cup \mathcal{P}_d^r$,$\mathcal{D}_o^r \cap \mathcal{P}_d^r = \emptyset$;
α_m	Set of all sites either with existing medical facilities or candidates for medical facilities for models I and III,$\alpha_m = \mathcal{M}_o \cup \mathcal{P}_m$,$\mathcal{M}_o \cap \mathcal{P}_m = \emptyset$;
T	Set of time points, $T = \{0,1,2,\ldots,n_t\}$;
F_0^{in}	Set of temporary medical facilities arriving at time point 0 of model implementation;

3.3.3 Parameters in Model I

The following are parameters used in model I. Like some of the sets previously provided, some of the parameters are also used in model II and/or model III and/or model IV.

t_{ik}	Estimated travel time (including loading-unloading time) from disaster area i to site k;
t_{jk}	Estimated travel time from site j to site k;
H_i	Estimated total number of injury-free victims in disaster area i (in number of people);

$W0_i$	Un-evacuated injured victims in disaster area $i$at the beginning of model implementation (in number of people);
g^1	Total amount of repeatedly-needed-commodity relief (or type-1-commodity relief) needed per time unit per person (in volume unit per person per time unit);
g^2	Total amount of once-and-for-all-commodity relief (or type-2-commodity relief) needed per person during planning horizon (in volume unit per person);
$I0_i^1$	Inventory level of type-1-commodity relief in disaster area $i$at the beginning of model implementation (in volume unit);
$G0_{ik}^2$	Total amount of type-2-commodity relief already sent from site k to disaster area i up to the beginning of model implementation (in volume unit);
p_g^1	Penalty for unmet type-1-commodity relief demand of a victim during a particular time period;
p_g^2	Penalty for unmet type-2-commodity relief demand of a victim during a particular time period;
p_h	Penalty for an un-evacuated injured victim during a particular time period;
f_{gh}	Conversion factor (in volume unit per person);
$Z0_k^{all}$	Number of vehicles already available at site $k$at the beginning of model implementation;
Cap	Capacity of each vehicle (in volume unit);
D	Time availability in one time period (in time unit);
M	A very big positive number;
N_{dc}^r	Maximum number of temporary distribution centres to establish in sub-region r;
V_g^{rin}	Number of new vehicles for commodity relief distribution becoming available at the beginning of model implementation in sub-region r;
V_g^{rout}	Number of vehicles for commodity relief distribution leaving sub-region r at the beginning of model implementation;

V_h^{in}	Number of new vehicles becoming available for victim evacuation at the beginning of model implementation;
V_h^{out}	Number of vehicles for victim evacuation leaving the disaster scene at the beginning of model implementation;

3.3.4 Variables in Model I

Decision variables used in model I or model III are defined below. Some of these decision variables will also be used in model II and/or model III and/or IV later.

XX	Maximum amongst the weighted unmet commodity relief demands in disaster areas in $A^r, r \in R$ during the planning horizon;
XY	Maximum amongthe weighted numbers of un-evacuated injured victims in disaster areas during the planning horizon;
S_{it}^1	Type-1-commodity relief shortages in disaster area i at time point t (in volume unit);
S_{it}^2	Type-2-commodity relief shortages in disaster area i at time point t (in volume unit);
W_{it}	Number of un-evacuated injured victims in disaster area i at time point t;
E_{ikt}	Number of injured victims evacuated from area i to site k in the period from time point t to $t + 1$;
I_{it}^1	Inventory level of type-1-commodity relief in disaster area i at time point t;
G_{ikt}^1	Total amount of type-1-commodity relief sent from site k to disaster area i in the period from time point t to t + 1 (in volume unit);
G_{ikt}^2	Total amount of type-2-commodity relief sent from site k to disaster area $i$in the period from time point t to t + 1 (in volume unit);

$$U_{jk} = \begin{cases} 1, \text{if medical facility } j \text{ is located to temporary site } k \\ 0, \text{otherwise} \end{cases}, \forall j \in F_0^{in};$$

$$Q_k^{open} = \begin{cases} 1, \text{if site } k \text{ is open} \\ 0, \text{otherwise} \end{cases};$$

$$U_k = \begin{cases} 1, \text{if temporary distribution centre is located to site } k \\ 0, \text{ otherwise} \end{cases};$$

$$Y_{ikt} = \begin{cases} 1, \text{if goods needed in area } i \text{ are sent from site } k \\ \quad \text{in the period from } t \text{ to } t+1 \\ 0, \text{otherwise} \end{cases} ;$$

$$X_{ikt} = \begin{cases} 1, \text{if injured victims in area } i \text{ are transported to site } k \\ \quad \text{in the period from time point } t \text{ to } t+1 \\ 0, \text{otherwise} \end{cases} ;$$

Z_{kt}^{all} Number of vehicles at site k from period t to $t+1$;

Z_{jkt}^{move} Number of vehicles already available at site j moved from site j to site k at time point t;

Z_{k}^{new} Number of new vehicles arriving at the beginning of model implementation assigned to site k;

Z_{k}^{leave} Number of vehicles leaving site k at the beginning of model implementation;

D_{ikt} Vehicle-time allocated/required for making trips between area i and site k in the period from time point t to $t+1$;

3.3.5 Sub-Model Ia: Commodity Relief Distribution

In model I, the commodity relief distributions in different sub-regions are performed independently. Model Ia is therefore for each sub-region r.

Objective function:

$$Min \left(|A^r| * XX + \sum_{i \in A^r} \sum_{t=1}^{n_t} \left(p_g^1 * S_{it}^1 + p_g^2 * t * S_{it}^2\right)\right) \qquad \text{... (0)}$$

The objective function of commodity relief distribution for model I - represented by (0) - is related to the weighted amount of unmet commodity relief demand, in each disaster area in the sub-region. While this quantity may be different for different areas, the objective is to minimize a weighted sum of the maximum among the quantities in the areas and the total quantity over all areas in the sub-region. The maximum is provided by constraints (1). The first term of this objective is in line with the commodity distribution policy made by the Ministry of Social Affairs in the region. In order to achieve the minimum value of the first term in the objective function without interference from the second term, the weight of the first term is set larger than that of the second term. The second term itself tries to minimise the total unmet commodity relief demand over all disaster areas within the sub-region without affecting the minimisation of the first term. The two terms represent the maximum and total victim suffering, respectively, due to the commodity relief shortage.

Subject to the following constraints:

Un-met commodity relief demands:

$$\sum_{t=1}^{n_t}(p_g^1 * S_{it}^1 + p_g^2 * t * S_{it}^2) \leq XX, \forall i \in A^r \qquad \text{... (1)}$$

As can be seen in constraints (1), un-met commodity relief demands in model I are weighted with penalty values. These values reflect the importance of each commodity type. Additionally, penalties for un-met type-2-commodity demands become higher over time. This will force model I to fulfil the type-2-commodity requirements as soon as possible.

Variable values at the first time point:

$$I_{i0}^1 = I0_i^1, \forall i \in A^r \qquad \text{... (2)}$$

$$Z_{jk0}^{move} = 0, \forall j \in \alpha_d^r, k \in \alpha_d^r \qquad \text{... (3)}$$

Inventory level of type-1-commodities at time point 0 for model I is defined in constraints (2). It is equal to the inventory level of the commodities at the beginning of model implementation. Constraints (3), meanwhile, relate to vehicle movement at the first time point of the first implementation of the model. These latter constraints, therefore, do not apply from the second implementation of the model onwards.

Constraints on commodity relief demands:

$$g^1 * (W_{it} + H_i) - I_{i,t-1}^1 - \sum_{k \in \alpha_d^r} G_{ik,t-1}^1 = S_{it}^1 - I_{it}^1, \forall i \in A^r, t \in T \backslash \{0\} \qquad \text{... (4)}$$

$$g^2 * (W_{it} + H_i) - \sum_{k \in \mathcal{D}_o^r} G0_{ik}^2 - \sum_{k \in \alpha_d^r} \sum_{\tau=0}^{t-1} G_{ik\tau}^2 \leq S_{it}^2, \quad \forall i \in A^r, t \in T \backslash \{0\} \qquad \text{... (5)}$$

$$2 * t_{ik} * (G_{ikt}^1 + G_{ikt}^2)/Cap \leq D_{ikt} + M * (1 - Y_{ikt}),$$

$$\forall i \in A^r, k \in \alpha_d^r,\ t \in T\backslash\{n_t\} \qquad \ldots (6)$$

$$G_{ikt}^1 + G_{ikt}^2 - M * Y_{ikt} \leq 0, \forall i \in A^r, k \in \alpha_d^r, t \in T\backslash\{n_t\} \qquad \ldots (7)$$

Constraints (4) determine the amount of type-1-commodity relief shortage in each disaster area at the end of each period. If the demand in the period is greater than or equal to the supply including the inventory at the beginning of the period and the amount distributed to the area during the period, then the difference will be the shortage and there will be no inventory at the end of the period. Otherwise, there will be some inventory left and no shortage.

Shortage of type-2-commodities at time point one onwards, on the other hand, cannot be less than the amount of the commodities required by un-evacuated injured victims and injury-free ones at the time point minus the total amount of the supplied commodities up to the point. Constraints (5) reflect this relation.

The amount of supplied commodities from a site to an area in a time period cannot exceed the commodity delivery capacity allocated between the two locations during the time period. Likewise, a site can supply commodities to a disaster area only if the area is allocated to the site. These requirements are formulated as constraints (6) and (7).

<u>Location of provisional sites:</u>

$$\sum_{k \in \mathcal{P}_d^r} U_k \leq N_{dc}^r \qquad \ldots (8)$$

Constraint (8) relate to the number of temporary sites with distribution centres to open at the beginning of the first implementation of the model. In this case, the total number of sites with distribution centres to open in a sub-region cannot exceed the maximum number of new distribution centres to establish for the sub-region. The constraints do not apply from the second model implementation onwards.

Allocation of disaster areas to sites:

$$\sum\nolimits_{i\in A^r} Y_{ikt} \le M * U_k, \forall k \in \mathcal{P}_d^r, t \in T\backslash\{n_t\} \qquad \dots (9)$$

$$\sum\nolimits_{k\in \alpha_d^r} Y_{ikt} = 1\ , \forall i \in A^r, t \in T\backslash\{n_t\} \qquad \dots (10)$$

Constraints (10) require that commodity relief demands in an area in a given time period are satisfied by exactly one site, and constraints (9) ensure that a site must be open in order for it to supply commodity relief. Because provisional sites with distribution centres are determined only once in the first implementation of the models, constraints (9) do not apply to subsequent implementations of the models. The opened sites will be treated as existing sites in the subsequent implementations.

Constraints on vehicle-time requirement in a particular site:

$$\sum\nolimits_{i\in A^r} D_{ikt} \le D * Z_{kt}^{all} - \sum\nolimits_{j\in \alpha_d^r}(t_{jk} * Z_{jkt}^{move}), \forall k \in \alpha_d^r,\ t \in T\backslash\{n_t\} \dots (11)$$

Vehicle-time requirement at a site with a distribution centre during a time period is defined by constraints (11). In the constraints, the vehicle-time requirement is determined by the total number of vehicles available at the site in the time period multiplied by the duration of the time period minus the number of vehicles moving from other sites to this site at the beginning of the time period multiplied by the time spent moving.

A special case appears in the first implementation of the model. That is, there are no vehicles moving in from other sites at that time.

Vehicle availability:

$$Z0_k^{all} + Z_k^{new} - Z_k^{leave} + \sum\nolimits_{j\in \alpha_d^r} Z_{jk0}^{move} - \sum\nolimits_{j\in \alpha_d^r} Z_{kj0}^{move} = Z_{k0}^{all}, \forall\ k \in \alpha_d^r \qquad \dots (12)$$

$$Z_{k,t-1}^{all} + \sum\nolimits_{j\in \alpha_d^r} Z_{jkt}^{move} - \sum\nolimits_{j\in \alpha_d^r} Z_{kjt}^{move} = Z_{kt}^{all}, \forall\ k \in \alpha_d^r, t \in T\backslash\{0, n_t\} \qquad \dots (13)$$

The number of vehicles available for commodity relief distribution at a given site from time point one onwards is determined by three different elements: (1) number of vehicles already available at the site, (2) number of vehicles moving into the site at the time point, and (3) number of vehicles moving out of the site at the point. Constraints (13) reflect this situation. Constraints (12), meanwhile, correspond to the number of relief distribution vehicles available in sites at time point 0. When the model is first implemented, there is neither vehicle movement nor leaving vehicles at time point 0.

<u>Vehicle out-movement:</u>

$$\sum_{k \in \alpha_d^r} Z_{jkt}^{move} = Z_{j,t-1}^{all}, \forall j \in \alpha_d^r,\ t \in T \backslash \{0, n_t\} \qquad \text{... (14)}$$

The number of vehicles for commodity relief distribution moving from a site to other sites (including those moving to the site itself, i.e., staying in the site) at the beginning of any particular time period (except the first time period) should be equal to the number of vehicles already available at the site in the previous time period. Constraints (14) reflect this necessity.

<u>Number of vehicles arriving and assigned to a particular site:</u>

$$\sum_{k \in \alpha_d^r} Z_k^{new} = V_g^{rin} \qquad \text{... (15)}$$

Vehicles arriving and available for relief distribution within a particular sub-region are always deployed to sites. Constraint (15) reflects the situation.

<u>Number of vehicles leaving from a particular site:</u>

$$\sum_{k \in \alpha_d^r} Z_k^{leave} = V_g^{rout} \qquad \text{... (16)}$$

The total number of vehicles for relief distribution leaving all sites with distribution centres in a sub-region at the beginning of any implementation of the model is equal to the number of relief distribution vehicles leaving the sub-region. This relationship is reflected by constraint (16).

Vehicles for commodity relief distribution leaving a site:

$Z_k^{leave} \ \leq \ Z0_k^{all}, \forall \ k \in \alpha_d^r$ ... (17)

The number of vehicles for relief distribution leaving a site at time point 0 of the model implementation cannot exceed the number of vehicles available at the site at the time point. Constraints (17) correspond to this necessity. The constraints are in line with the requirement that any vehicle cannot arrive at and leave a site at the same time.

Relation between vehicle deployment and existence of site:

$Z_{kt}^{all} - \ M * U_k \leq 0 \ , \forall k \in \mathcal{P}_d^r, t \in T \backslash \{n_t\}$ ... (18)

The deployment of commodity relief distribution vehicles to a particular site is carried out only if the site is open. Otherwise, the number of vehicles allocated to the site is forced to be zero. Constraints (18) reflect the requirement. The constraints apply to the first implementation of the models only.

Non-negative variables:

$XX \ \geq 0$ ... (non_1)

$S_{it}^1 \ \geq 0, \forall i \in A^r, t \in T \backslash \{0\}$ ... (non_2)

$S_{it}^2 \ \geq 0, \forall \ i \in A^r, t \in T \backslash \{0\}$ ... (non_3)

$I_{it}^1 \ \geq 0 \ , \forall A^r, t \in T$ ... (non_4)

$G_{ikt}^1 \geq 0, \forall \ i \in A^r, k \in \alpha_d^r, t \in T \backslash \{n_t\}$ ... (non_5)

$G_{ikt}^2 \geq 0, \forall \ i \in A^r, k \in \alpha_d^r, t \in T \backslash \{n_t\}$ ... (non_6)

$D_{ikt} \geq 0, \forall i \in A^r, k \in \alpha_d^r, t \in T \backslash \{n_t\}$ ... (non_7)

Integer variables:

$Z_{kt}^{all} \geq 0$ and integer, $\forall k \in \alpha_d^r, t \in T \backslash \{n_t\}$ ... (int_1)

$Z_{jkt}^{move} \geq \ 0$ and integer, $\forall j \in \alpha_d^r, k \in \alpha_d^r, t \in T \backslash \{n_t\}$ ... (int_2)

$Z_k^{new} \geq 0$ and integer, $\forall k \in \alpha_d^r$ ... (int_3)

$Z_k^{leave} \geq 0$ and integer, $\forall k \in \alpha_d^r$ ... (int_4)

Binary variables:

$Y_{ikt} = 0 \; or \; 1, \forall i \in A^r, k \in \alpha_d^r, t \in T \backslash \{n_t\}$ ... (bin_1)

$U_k = 0 \; or \; 1, \forall k \in \mathcal{P}_d^r$ ... (bin_2)

3.3.6 Sub-Model Ib: Victim Evacuation

Objective function:

$$Min \left(|A| * XY + \sum_{i \in A} \sum_{t=1}^{n_t} (p_h * t * W_{it})\right) \quad \text{... (20)}$$

The objective of sub-model Ib is to minimize the weighted sum of the maximum suffering and total suffering of the un-evacuated injured victims in disaster areas. The suffering here refers to the delay in evacuation. Again, a larger weight is assigned to the first term than that to the second term to make sure the maximum suffering is minimized first in the optimal solution.

Subject to the following constraints:

Un-evacuated injured victims in disaster areas:

$$\sum_{t=1}^{n_t} p_h * t * W_{it} \le XY, \forall i \in A \quad \text{... (21)}$$

The maximum weighted number of un-evacuated victims during the planning horizon (i.e. maximum suffering) is always greater than or equal to the weighted number of un-evacuated victims in any area. Constraints (21) represent this relation.

Several variable values at the first time point:

$W_{i0} = W0_i, \forall i \in A$ ... (22)

$Z_{jk0}^{move} = 0, \forall j \in \alpha_m, k \in \alpha_m$ ... (23)

The number of un-evacuated injured victims at the first time point is defined in constraints (22). The number is equal to the number of un-evacuated victims at the beginning of model implementation. Constraints (23), which only apply to the first implementation of the model, represent vehicle movement at the first time point.

Constraints on victim evacuation demands:

$$W_{it} = W_{i,t-1} - \sum_{k \in \alpha_m} E_{ik,t-1}, \forall i \in A, t \in T \backslash \{0\} \qquad \text{... (24)}$$

$$2 * f_{gh} * t_{ik} * E_{ikt}/Cap \leq D_{ikt} + M * (1 - X_{ikt}), \qquad \forall i \in A, k \in \alpha_m, t \in T \backslash \{n_t\} \qquad \text{... (25)}$$

$$E_{ikt} - M * X_{ikt} \leq 0, \forall i \in A, k \in \alpha_m, t \in T \backslash \{n_t\} \qquad \text{... (26)}$$

Constraints (24) state that the number of un-evacuated victims in an area at a given time point is equal to the number of un-evacuated victims at the previous point minus the number of evacuated victims between these two time points. Constraints (25), in the meantime, insist that the capacity of a particular site to transport injured victims from an area during a time period cannot be exceeded by the number of injured victims received by the site from the area in the period. Constraints (26) require that the number of evacuated victims for any unconnected site-area pair in the sub-models is zero.

Deployment of temporary medical facilities to sites:

$$\sum_{k \in \mathcal{P}_m} U_{jk} \leq 1, \forall j \in F_0^{in} \qquad \text{... (27)}$$

Constraints (27) indicate that a temporary medical facility is deployed to at most one temporary site.

Location of provisional sites:

$$Q_k^{open} \leq \sum_{j \in F_0^{in}} U_{jk}, \forall k \in \mathcal{P}_m \qquad \text{... (28)}$$

$$M * Q_k^{open} \geq \sum_{j \in F_0^{in}} U_{jk}, \forall k \in \mathcal{P}_m \qquad \text{... (29)}$$

Constraints (28) and (29) relate to medical facilities arriving at the beginning of the model implementation. In this sense, a provisional site is open for medical services when there is at least one temporary medical facility allocated to it.

Allocation of disaster areas to sites:

$$\sum_{i \in A} X_{ikt} \leq M * Q_k^{open}, \forall k \in \mathcal{P}_m, t \in T \backslash \{n_t\} \qquad \text{... (30)}$$

$$\sum_{k \in \alpha_m} X_{ikt} = 1 , \forall i \in A, t \in T \backslash \{n_t\} \qquad \text{... (31)}$$

Constraints (31) require that, in a given time period, injured victims in an area are evacuated to exactly one site. In addition, constraints (30) necessitate that the evacuation must be to a site that is open.

Constraints on vehicle-time requirement in a particular site:

$$\sum_{i \in A} D_{ikt} \leq D * Z_{kt}^{all} - \sum_{j \in \alpha_m} (t_{jk} * Z_{jkt}^{move}), \forall k \in \alpha_m,\ t \in T \backslash \{n_t\} \qquad \text{... (32)}$$

Vehicle-time requirement for a site with a medical facility to conduct evacuation during any time period is defined by constraints (32). Similar to constraints (11) of sub-model Ia, the vehicle-time requirement is determined by the number of vehicles available at the site in the time period multiplied by the duration of the time period minus the number of vehicles moving from other sites to this site multiplied by the time spent on the moving.

Again, a special case appears in the first implementation of the model. That is, there are no vehicles moving in from other sites at that time.

Vehicle availability for victim evacuation:

$$Z0_k^{all} + Z_k^{new} - Z_k^{leave} + \sum_{j \in \alpha_m} Z_{jk0}^{move} - \sum_{j \in \alpha_m} Z_{kj0}^{move} = Z_{k0}^{all}, \forall\ k \in \alpha_m \qquad \text{... (33)}$$

$$Z_{k,t-1}^{all} + \sum_{j \in \alpha_m} Z_{jkt}^{move} - \sum_{j \in \alpha_m} Z_{kjt}^{move} = Z_{kt}^{all}, \forall\ k \in \alpha_m, t \in T \backslash \{0, n_t\} \qquad \text{... (34)}$$

Vehicle availability for victim evacuation is defined by constraints (33) and (34). The explanations are similar to those for constraints (12) and (13).

Vehicle out-movement:

$$\sum_{k\in\alpha_m} Z_{jkt}^{move} = Z_{j,t-1}^{all}, \forall j \in \alpha_m,\ t \in T\backslash\{0, n_t\} \quad \text{... (35)}$$

Requirement on vehicle out-movement of sub-model Ib is provided by constraints (35). Analogous with constraint (14) of sub-model Ia, the total number of evacuation vehicles moving out of a site to all sites (including those moving to the site itself, i.e., staying in the site) at a given time point (except time point 0 and the last time point) is equal to the number of evacuation vehicles available at the site in the period.

Number of vehicles arriving and assigned to a site:

$$\sum_{k\in\alpha_m} Z_k^{new} = V_h^{in} \quad \text{... (36)}$$

Constraint (36) requires that the total number of vehicles for victim evacuation arriving at the beginning of the model implementation and assigned to all sites are exactly equal to the number of available vehicles.

Number of vehicles leaving a site:

$$\sum_{k\in\alpha_m} Z_k^{leave} = V_h^{out} \quad \text{... (37)}$$

The total number of vehicles for victim evacuation leaving all sites with medical facilities is exactly the same as the number of victim evacuation vehicles leaving the disaster scene. Constraint (37) indicates the requirement.

Vehicles leaving from a particular site:

$$Z_k^{leave} \le Z0_k^{all}, \forall\ k \in \alpha_m \quad \text{... (38)}$$

The number of vehicles for victim evacuation already available at a site at the beginning of the model implementation cannot be exceeded by the number of vehicles leaving the site at that time point. Constraints (38) reflect this requirement.

Relation between vehicle deployment and existence of site:

$$Z_{kt}^{all} - M * U_{k}^{open} \leq 0 \text{ , } \forall k \in \mathcal{P}_m, t \in T\backslash\{n_t\} \quad \text{... (39)}$$

Constraints (39) necessitate that the deployment of evacuation vehicles to a site is carried out only if the site is open.

Non-negative variables:

$$XY \geq 0 \quad \text{... (non\_8)}$$
$$W_{it} \geq 0, \forall i \in A, t \in T \quad \text{... (non\_9)}$$
$$E_{ikt} \geq 0, \forall i \in A, k \in \alpha_m, t \in T\backslash\{n_t\} \quad \text{... (non\_10)}$$
$$D_{ikt} \geq 0, \forall i \in A, k \in \alpha_m, t \in T\backslash\{n_t\} \quad \text{... (non\_11)}$$

Integer variables:

$$Z_{kt}^{all} \geq 0 \text{ and integer, } \forall k \in \alpha_m, t \in T\backslash\{n_t\} \quad \text{... (int\_5)}$$
$$Z_{jkt}^{move} \geq 0 \text{ and integer, } \forall j \in \alpha_m, k \in \alpha_m, t \in T\backslash\{n_t\} \quad \text{... (int\_6)}$$
$$Z_{k}^{new} \geq 0 \text{ and integer,} \forall k \in \alpha_m \quad \text{... (int\_7)}$$
$$Z_{k}^{leave} \geq 0 \text{ and integer, } \forall k \in \alpha_m \quad \text{... (int\_8)}$$

Binary variables:

$$X_{ikt} = 0 \text{ or } 1, \forall i \in A, k \in \alpha_m, t \in T\backslash\{n_t\} \quad \text{... (bin\_3)}$$
$$U_{jk} = 0 \text{ or } 1, \forall j \in F_0^{in}, k \in \mathcal{P}_m \quad \text{... (bin\_4)}$$
$$Q_{k}^{open} = 0 \text{ or } 1, \forall k \in \mathcal{P}_m \quad \text{... (bin\_5)}$$

3.4 Model III

Model III is one of proposed location-allocation models intended to realize the potential for improvement in the presence of a National Board for Disaster Management and its derivatives at several levels. It is based on model I, but takes future information on resource availability into consideration, while keeping commodity relief distribution and victim evacuation separate.

In many instances of disaster management, some future information with respect to resource availability can be obtained in advance with adequate certainty. Examples of such information include the numbers of incoming medical facilities and incoming vehicles, as well as the time they will arrive at and depart from the disaster scene.

Because of the inclusion of future information, the fact that incoming medical facilities as well as incoming vehicles are able to leave the scene within the planning horizon affects the way the problem is formulated. One of the effects is the need to re-define variables providing information about the functioning and closure of temporary sites. Variables are also needed to represent the number of already-allocated-vehicles departing from a site.

Similar to model I, model III consists of two sub-models. Sub-model IIIa deals with commodity relief distribution, while victim evacuation is addressed by sub-model IIIb. The corresponding sub-models in the two models also share similar structures with some constraints being the same.

3.4.1 Additional Assumptions of Model III

There are also several additional assumptions for model III. These additional assumptions are as follows.

With the coordination of the National Board for Disaster Management and its derivatives, the boundaries of the sub-regions should not be restrictive for the evacuation and distribution activities. Therefore, division of the region into sub-regions is not considered in model III. As a consequence, the commodity demand in a particular disaster area can be fulfilled by any site with a distribution centre. Injured victims in the area, in the meantime, can be transported to any site with a medical facility.

It is possible that the departure times of medical facilities (of which arrival times are known in advance) are either not known beforehand or uncertain. In this case, these incoming medical facilities are assumed to be able to stay in the disaster scene during the planning horizon.

It is likely that, as time goes on, information on resources changes. Model III is re-run every time these changes occur. Examples of this situation are changes in terms of the number of vehicles available at particular time points, when and how many incoming medical facilities already considered will arrive at and leave from the disaster scene, and when and how many other incoming medical facilities will arrive at and depart from the scene.

3.4.2 Sets Used in Model III

Sets used in mathematical model III are as follows. As it can be seen later, some of these sets are also used in model II and/or model IV. Other sets appear in the model have already been defined in the section associated with model I and, therefore, do not need to be explained again.

$\mathcal{D}_o$	Set of all existing sites with distribution centres but not allowed to have medical facilities, $\mathcal{D}_o = \bigcup_{r \in R} \mathcal{D}_o^r$;
$\mathcal{P}_d$	Set of candidate sites for temporary distribution centres, $\mathcal{P}_d = \bigcup_{r \in R} \mathcal{P}_d^r$;
α_d	Set of all sites either with existing distribution centres or candidates for distribution centres, $\alpha_d = \mathcal{D}_o \cup \mathcal{P}_d, \mathcal{D}_o \cap \mathcal{P}_d = \emptyset$;
F_t^{in}	Set of temporary medical facilities arriving at time point $t \in T \backslash \{n_t\}$;
F_t^{out}	Set of temporary medical facilities leaving the disaster scene at time point $t \in T \backslash \{n_t\}$;

3.4.3 Parameters in Model III

The following are parameters used in model III. Like some of the sets previously provided, some of the parameters are also used in model II and/or model IV. Other parameters, in the meantime, have already been described in Section 3.3.

N_{dc}	Maximum number of temporary distribution centres to establish;
V_{gt}^{in}	Number of new vehicles becoming available for commodity relief distribution at time point t;

V_{gt}^{out}	Number of vehicles for relief distribution leaving the disaster scene at time point t;
V_{ht}^{in}	Number of new vehicles becoming available for victim evacuation at time point t;
V_{ht}^{out}	Number of vehicles for victim evacuation leaving the disaster scene at time point t;

3.4.4 Variables in Model III

Decision variables used in model III are defined below.Other decision variables have already been defined in association with model I and, therefore, will not be described again in the current part.

YY	Maximum among the weighted un-met commodity relief demands in all disaster areas during the planning horizon;

$U_{jk} = \begin{cases} 1, \text{if medical facility } j \text{ is located to temporary site } k \\ 0, \text{otherwise} \end{cases}, \forall j \in F_t^{in};$

$Q_{kt}^{open} = \begin{cases} 1, \text{if site } k \text{ is open from time point } t \text{ to } t+1 \\ 0, \text{otherwise} \end{cases};$

Z_{kt}^{new}	Number of vehicles arriving at time point t assigned to site k;
Z_{kt}^{leave}	Number of vehicles leaving site k at time point t;

3.4.5 Sub-Model IIIa: Commodity Relief Distribution

Unlike sub-model Ia, this sub-model is for the whole region including all sub-regions.

Objective function:

$$Min\left(|A| * YY + \sum_{i\in A}\sum_{t=1}^{n_t}\left(p_g^1 * S_{it}^1 + p_g^2 * t * S_{it}^2\right)\right) \quad \ldots (40)$$

As for sub-model Ia, the objective of this sub-model is to minimize the weighted sum of maximum suffering and total suffering due to commodity relief shortage, with the maximum suffering as the primary concern.

Subject to the following constraints:

$\sum_{t=1}^{n_t} \left(p_g^1 * S_{it}^1 + p_g^2 * t * S_{it}^2\right) \leq YY, \forall i \in A$ ... (41)

$I_{i0}^1 = I0_i^1, \forall i \in A$ ... (42)

$Z_{jk0}^{move} = 0, \forall j \in \alpha_d, k \in \alpha_d$ ... (43)

$g^1 * (W_{it} + H_i) - I_{i,t-1}^1 - \sum_{k\in\alpha_d} G_{ik,t-1}^1 = S_{it}^1 - I_{it}^1, \forall i \in A, t \in T\backslash\{0\}$ ... (44)

$g^2 * (W_{it} + H_i) - \sum_{k\in\mathcal{D}_o} G0_{ik}^2 - \sum_{k\in\alpha_d} \sum_{\tau=0}^{t-1} G_{ik\tau}^2 \leq S_{it}^2, \forall i \in A, t \in T\backslash\{0\}$ ... (45)

$2 * t_{ik} * (G_{ikt}^1 + G_{ikt}^2)/Cap \leq D_{ikt} + M * (1 - Y_{ikt}), \quad \forall i \in A, k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (46)

$G_{ikt}^1 + G_{ikt}^2 - M * Y_{ikt} \leq 0, \forall i \in A, k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (47)

$\sum_{k\in\mathcal{P}_d} U_k \leq N_{dc}$ ... (48)

$\sum_{i\in A} Y_{ikt} \leq M * U_k, \forall k \in \mathcal{P}_d, t \in T\backslash\{n_t\}$ ... (49)

$\sum_{k\in\alpha_d} Y_{ikt} = 1, \forall i \in A, t \in T\backslash\{n_t\}$ ... (50)

$\sum_{i\in A} D_{ikt} \leq D * Z_{kt}^{all} - \sum_{j\in\alpha_d} (t_{jk} * Z_{jkt}^{move}), \forall k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (51)

$Z0_k^{all} + Z_{k0}^{new} - Z_{k0}^{leave} + \sum_{j\in\alpha_d} Z_{jk0}^{move} - \sum_{j\in\alpha_d} Z_{kj0}^{move} = Z_{k0}^{all}, \forall k \in \alpha_d$ ... (52)

$Z_{k,t-1}^{all} + Z_{kt}^{new} - Z_{kt}^{leave} + \sum_{j\in\alpha_d} Z_{jkt}^{move} - \sum_{j\in\alpha_d} Z_{kjt}^{move} = Z_{kt}^{all}, \quad \forall k \in \alpha_d, t \in T\backslash\{0, n_t\}$ ... (53)

$\sum_{k\in\alpha_d} Z_{jkt}^{move} = Z_{j,t-1}^{all}, \forall j \in \alpha_d, t \in T\backslash\{0, n_t\}$ ... (54)

$\sum_{k\in\alpha_d} Z_{kt}^{new} = V_{gt}^{in}, \forall t \in T\backslash\{n_t\}$ ... (55)

$\sum_{k\in\alpha_d} Z_{kt}^{leave} = V_{gt}^{out}, \forall t \in T\backslash\{n_t\}$ ... (56)

$Z_{k0}^{leave} \leq Z0_k^{all}, \forall k \in \alpha_d$ ... (57)

$Z_{kt}^{leave} \leq Z_{k,t-1}^{all}, \forall k \in \alpha_d, t \in T\backslash\{0, n_t\}$ ... (58)

$Z_{kt}^{all} - M * U_k \leq 0, \forall k \in \mathcal{P}_d, t \in T\backslash\{n_t\}$ ... (59)

$YY \geq 0$ ... (non_12)

$S_{it}^1 \geq 0, \forall i \in A, t \in T\backslash\{0\}$ ... (non_13)

$S_{it}^2 \geq 0, \forall i \in A, t \in T\backslash\{0\}$ ... (non_14)

$I_{it}^1 \geq 0, \forall i \in A, t \in T$ ... (non_15)

$G^{1}_{ikt} \geq 0, \forall\, i \in A,\ k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (non_16)

$G^{2}_{ikt} \geq 0, \forall\, i \in A,\ k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (non_17)

$D_{ikt} \geq 0, \forall i \in A, k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (non_18)

$Z^{all}_{kt} \geq 0$ and integer, $\forall k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (int_9)

$Z^{move}_{jkt} \geq 0$ and integer, $\forall j \in \alpha_d, k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (int_12)

$Z^{new}_{kt} \geq 0$ and integer, $\forall k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (int_10)

$Z^{leave}_{kt} \geq 0$ and integer, $\forall k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (int_11)

$Y_{ikt} = 0 \text{ or } 1, \forall i \in A, k \in \alpha_d, t \in T\backslash\{n_t\}$ ... (bin_6)

$U_k = 0 \text{ or } 1, \forall k \in \mathcal{P}_d$ ... (bin_7)

In this model, constraints (41) – (57) are for purposes similar to those of constraints (1) – (17), respectively, in sub-model Ia. The main difference is that constraints here are for the whole region, while the constraints in sub-model Ia are for one sub-region r. Another difference between the two models is that sub-model IIIa considers further resource availability. This is reflected by the Z variables in the above constraints and the additional constraints (58) and (59). The rest constraints are standard non-negativity and integer constraints.

3.4.6 Sub-Model IIIb: Victim Evacuation

Objective function:

Objective expression (20)

Subject to the following constraints:

Constraints (21)-(26), (31), (32), (35), (non_8)-(non_11), (int_5)-(int_6), (bin_3), and

$\sum_{k \in \mathcal{P}_m} U_{jk} \leq 1, \forall j \in F^{in}_t, t \in T\backslash\{n_t\}$ ... (61)

$Q^{open}_{kt} \leq \sum_{\tau=0}^{t} \sum_{j \in F^{in}_\tau} U_{jk} - \sum_{\tau=0}^{t} \sum_{j \in F^{out}_\tau} U_{jk}, \forall k \in \mathcal{P}_m, t \in T\backslash\{n_t\}$

... (62)

$M * Q^{open}_{kt} \geq \sum_{\tau=0}^{t} \sum_{j \in F^{in}_\tau} U_{jk} - \sum_{\tau=0}^{t} \sum_{j \in F^{out}_\tau} U_{jk}, \forall k \in \mathcal{P}_m, t \in T\backslash\{n_t\}$

... (63)

$\sum_{i \in A} X_{ikt} \leq M * Q^{open}_{kt}, \forall k \in \mathcal{P}_m, t \in T\backslash\{n_t\}$ ... (64)

$Z0_k^{all} + Z_{k0}^{new} - Z_{k0}^{leave} + \sum_{j\in\alpha_m} Z_{jk0}^{move} - \sum_{j\in\alpha_m} Z_{kj0}^{move} = Z_{k0}^{all}, \forall\, k \in \alpha_m$ ... (65)

$Z_{k,t-1}^{all} + Z_{kt}^{new} - Z_{kt}^{leave} + \sum_{j\in\alpha_m} Z_{jkt}^{move} - \sum_{j\in\alpha_m} Z_{kjt}^{move} = Z_{kt}^{all}, \quad \forall\, k \in \alpha_m, t \in T\backslash\{0, n_t\}$ ... (66)

$\sum_{k\in\alpha_m} Z_{kt}^{new} = V_{ht}^{in}, \forall t \in T\backslash\{n_t\}$ ... (67)

$\sum_{k\in\alpha_m} Z_{kt}^{leave} = V_{ht}^{out}, \forall t \in T\backslash\{n_t\}$ ... (68)

$Z_{k0}^{leave} \leq Z0_k^{all}, \forall\, k \in \alpha_m$ ... (69)

$Z_{kt}^{leave} \leq Z_{k,t-1}^{all}, \forall\, k \in \alpha_m, t \in T\backslash\{0, n_t\}$ ... (70)

$Z_{kt}^{all} - M * Q_{kt}^{open} \leq 0, \forall k \in \mathcal{P}_m, t \in T\backslash\{n_t\}$ ... (71)

$Z_{kt}^{new} \geq 0$ and integer, $\forall k \in \alpha_m, t \in T\backslash\{n_t\}$ ... (int_13)

$Z_k^{leave} \geq 0$ and integer, $\forall k \in \alpha_m$ ... (int_14)

$Z_{kt}^{leave} \geq 0$ and integer, $\forall k \in \alpha_m, t \in T\backslash\{n_t\}$ ... (int_15)

$U_{jk} = 0$ or $1, \forall j \in F_t^{in}, k \in \mathcal{P}_m, t \in T\backslash\{n_t\}$ ...(bin_8)

$Q_{kt}^{open} = 0$ or $1, \forall k \in \mathcal{P}_m, t \in T\backslash\{n_t\}$ ... (bin_9)

Constraints (61) – (71) are similar to some constraints in sub-model Ib. However, the constraints here allow new resources to be deployed and existing resources to leave the scene at later time points after time point 0.

3.5 Model II

Similar to model III, model II is proposed to realize the potential for improvement in the presence of a National Board for Disaster Management and its derivatives at several levels. Again, this model is intended to improve the performance of the 'current-practice' location-allocation model. The model is mainly characterised by allowing commodity relief distribution and victim evacuation carried out jointly by sharing vehicles.

3.5.1 Additional Assumptions

Additional assumptions of model II are provided below.

The commodity demand in a particular disaster area can be fulfilled by any site with a distribution centre. Injured victims in the area, in the meantime, can be transported to any site with a medical facility.

In most situations, existing sites with medical facilities have to provide medical services for regular medical problems. The addition of services for disaster victims raises a certain level of managerial and operational complexity. In this regard, this type of site only functions as destinations for injured victim evacuation. It is possible, nonetheless, for some sites with existing medical facilities to be capable of functioning as a distribution centre as well. This may be due to their wide area or the presence of a sports stadium nearby, for instance.

Similarly, existing sites with distribution centres fall into two different categories, i.e. with and without the capability to host a temporary medical facility as well.

The locations of all abovementioned sites are known.

The potential sites for temporary facilities (which function either as distribution centres or provisional medical facilities or both) are known.

Vehicles allocated to a site with a distribution centre in a time period are allowed to go through sites with a medical facility during their journey between a site and a disaster area. Vehicles allocated to a site with a medical facility only during a time period, on the other hand, are not permitted to go through any other sites during their journey.

Model II still shares some features with model I. Among these features is the exclusion of future information. Similar to model I, model II is run repeatedly every time new information arises. Outputs resulting from the implementation of the model in the first run will be used as inputs for the second run, etc.

3.5.2 Sets in Model II

In addition to sets that have been defined in Section 3.3 and Section 3.4, the followings are other sets used in mathematical model II.

$\mathcal{D}$	Set of existing sites with distribution centres and allowed to have medical facilities;
$\mathcal{M}$	Set of existing sites with medical facilities and allowed to have distribution centres;
$\mathcal{B}$	Set of sites with both distribution centres and medical facilities;
$\mathcal{P}_b$	Set of candidate sites for both temporary distribution centres and temporary medical facilities;
δ_d	Set of all potential sites for new distribution centres in models II and IV, $\delta_d = \mathcal{M} \cup \mathcal{P}_d \cup \mathcal{P}_b, \mathcal{M} \cap \mathcal{P}_d \cap \mathcal{P}_b = \emptyset$;
δ_m	Set of all potential sites for new medical facilities in models II and IV, $\delta_m = \mathcal{D} \cup \mathcal{P}_m \cup \mathcal{P}_b, \mathcal{D} \cap \mathcal{P}_m \cap \mathcal{P}_b = \emptyset$;
β_d	Set of all sites either with existing distribution centres or candidates for distribution centres in models II and IV, $\beta_d = \mathcal{D}_o \cup \mathcal{D} \cup \mathcal{B} \cup \mathcal{M} \cup \mathcal{P}_d \cup \mathcal{P}_b, \mathcal{D}_o \cap \mathcal{D} \cap \mathcal{B} \cap \mathcal{M} \cap \mathcal{P}_d \cap \mathcal{P}_b = \emptyset$;
β_m	Set of all sites either with existing medical facilities or candidates for medical facilities in models II and IV, $\beta_m = \mathcal{M}_o \cup \mathcal{M} \cup \mathcal{B} \cup \mathcal{D} \cup \mathcal{P}_m \cup \mathcal{P}_b, \mathcal{M}_o \cap \mathcal{M} \cap \mathcal{B} \cap \mathcal{D} \cap \mathcal{P}_m \cap \mathcal{P}_b = \emptyset$;
$\mathcal{E}_d$	Set of all sites with existing distribution centres in models II and IV, $\mathcal{E}_d = \mathcal{D}_o \cup \mathcal{D} \cup \mathcal{B}, \mathcal{D}_o \cap \mathcal{D} \cap \mathcal{B} = \emptyset$;
$\mathcal{L}$	Set of all sites in models II and IV, $\mathcal{L} = \mathcal{D}_o \cup \mathcal{D} \cup \mathcal{M}_o \cup \mathcal{M} \cup \mathcal{B} \cup \mathcal{P}_d \cup \mathcal{P}_m \cup \mathcal{P}_b, \mathcal{D}_o \cap \mathcal{D} \cap \mathcal{M}_o \cap \mathcal{M} \cap \mathcal{B} \cap \mathcal{P}_d \cap \mathcal{P}_m \cap \mathcal{P}_b = \emptyset$;

3.5.3 Parameters in Model II

What follow are parameters used in model II. Otherwise stated in this section, explanation on parameters appearing in the mathematical model formulation can be found in Section 3.3 and Section 3.4.

V^{in}	Number of new vehicles becoming available at the beginning of model implementation;
V^{out}	Number of vehicles leaving thedisaster sceneat the beginning of model implementation.

3.5.4 Variables in Model II

The followings are decision variables used in model II along with their definitions. Some of the other variables in the model have already appeared in models I and III and, therefore, do not need any description.

ZZ	Maximum among the sums of weighted number of un-evacuated injured victims and the weighted unmet commodity relief demands during the planning horizon;
$\bar{E}_{ikt}$	Number of injured victims evacuated from area i directly to site k in the period from time point t to $t+1$;
$\tilde{E}_{ikt}$	Number of injured victims evacuated from area i to site k by vehicles that are allocated to another site j but going through site k in the period from time point t to $t+1$;
$\bar{G}_{ikt}^{1}$	Total amount of type-1-commodity relief sent from site k directly to disaster area i in the period from time point t to $t+1$ (in volume unit);
$\tilde{G}_{ikt}^{1}$	Total amount of type-1-commodity relief sent from site k to disaster area i by vehicles going through site j in the period from time point t to $t+1$ (in volume unit);
$\bar{G}_{ikt}^{2}$	Total amount of type-2-commodity relief sent from site k directly to disaster area i in the period from time point t to $t+1$ (in volume unit);
$\tilde{G}_{ikt}^{2}$	Total amount of type-2-commodity relief sent from site k to disaster area i by vehicles going through site j in period from time point t to $t+1$ (in volume unit);

3.5.5 Mathematical Model

Objective function:

$$Min\left(|A| * ZZ + \sum_{i\in A}\sum_{t=1}^{n_t}\left(p_h * t * f_{gh} * W_{it} + p_g^1 * S_{it}^1 + p_g^2 * t * S_{it}^2\right)\right) \qquad \text{... (80)}$$

The objective in the models is again to minimize the weighted sum of maximum suffering and total suffering with maximum suffering as the primary concern. The suffering in this model considers both those due to waiting for evacuation and those due to commodity relief shortage.

Subject to the following constraints:

Constraints (22), (42), (non_9), (non_13)-(non_15), and

$\sum_{t=1}^{n_t}\left(p_h * t * f_{gh} * W_{it} + p_g^1 * S_{it}^1 + p_g^2 * t * S_{it}^2\right) \leq ZZ, \forall i \in A$ ... (81)

$Z_{jk0}^{move} = 0, \forall j \in \mathcal{L}, k \in \mathcal{L}$ ... (82)

$g^1 * (W_{it} + H_i) - I_{i,t-1}^1 - \sum_{k \in \beta_d}(\bar{G}_{ik,t-1}^1 + \tilde{G}_{ik,t-1}^1) = S_{it}^1 - I_{it}^1, \quad \forall i \in$
$A, t \in T\backslash\{0\}$ ... (83)

$g^2 * (W_{it} + H_i) - \sum_{k \in \mathcal{E}_d} G0_{ik}^2 - \sum_{k \in \beta_d} \sum_{\tau=0}^{t-1}(\bar{G}_{ik\tau}^2 + \tilde{G}_{ik\tau}^2) \leq S_{it}^2,$
$\forall i \in A, t \in T\backslash\{0\}$ ... (84)

$2 * t_{ik} * (\bar{G}_{ikt}^1 + \bar{G}_{ikt}^2)/Cap + \left(t_{ik} + t_{kj} + t_{ji}\right) * \left(\tilde{G}_{ikt}^1 + \tilde{G}_{ikt}^2\right)/Cap \leq D_{ikt} +$
$M * (2 - Y_{ikt} - X_{ijt}), \forall i \in A, k \in \beta_d, j \in \beta_m, t \in T\backslash\{n_t\}$ ... (85)

$2 * t_{ik} * (\bar{G}_{ikt}^1 + \bar{G}_{ikt}^2)/Cap + \left(t_{ik} + t_{kj} + t_{ji}\right) * f_{gh} * \tilde{E}_{ijt}/Cap \leq D_{ikt} +$
$M * (2 - Y_{ikt} - X_{ijt}), \forall i \in A, k \in \beta_d, j \in \beta_m, t \in T\backslash\{n_t\}$ ... (86)

$\bar{G}_{ikt}^1 + \bar{G}_{ikt}^2 + \tilde{G}_{ikt}^1 + \tilde{G}_{ikt}^2 - M * Y_{ikt} \leq 0, \forall i \in A, k \in \beta_d, t \in T\backslash\{n_t\}$
... (87)

$W_{it} = W_{i,t-1} - \sum_{k \in \beta_m}(\bar{E}_{ik,t-1} + \tilde{E}_{ik,t-1}), \forall i \in A, t \in T\backslash\{0\}$ ... (88)

$2 * f_{gh} * t_{ik} * \bar{E}_{ikt}/Cap \leq D_{ikt} + M * (1 - X_{ikt}), \quad \forall i \in A, k \in \beta_m, t \in$
$T\backslash\{n_t\}$ ... (89)

$\bar{E}_{ikt} + \tilde{E}_{ikt} - M * X_{ikt} \leq 0, \forall i \in A, k \in \beta_m, t \in T\backslash\{n_t\}$ ... (90)

$\sum_{k \in \delta_m} U_{jk} \leq 1, \forall j \in F_0^{in}$ ... (91)

$Q_k^{open} \leq \sum_{j \in F_0^{in}} U_{jk}, \forall k \in \delta_m$ ... (92)

$M * Q_k^{open} \geq \sum_{j \in F_0^{in}} U_{jk}, \forall k \in \delta_m$ ... (93)

$\sum_{k \in \delta_d} U_k \leq N_{dc}$ ... (94)

$\sum_{i \in A} Y_{ikt} \leq M * U_k, \forall k \in \delta_d, t \in T\backslash\{n_t\}$ ... (95)

$\sum_{k \in \beta_d} Y_{ikt} = 1, \forall i \in A, t \in T\backslash\{n_t\}$ ... (96)

$\sum_{i \in A} X_{ikt} \leq M * Q_k^{open}, \forall k \in \delta_m, t \in T\backslash\{n_t\}$ ... (97)

$\sum_{k \in \beta_m} X_{ikt} = 1, \forall i \in A, t \in T\backslash\{n_t\}$ ... (98)

$\sum_{i \in A} D_{ikt} \leq D * Z_{kt}^{all} - \sum_{j \in \mathcal{L}}(t_{jk} * Z_{jkt}^{move}), \forall k \in \mathcal{L}, t \in T\backslash\{n_t\}$ ... (99)

$Z0_k^{all} + Z_k^{new} - Z_k^{leave} + \sum_{j \in \mathcal{L}} Z_{jk0}^{move} - \sum_{j \in \mathcal{L}} Z_{kj0}^{move} = Z_{k0}^{all}, \forall\, k \in \mathcal{L}$... (100)

$Z_{k,t-1}^{all} + \sum_{j \in \mathcal{L}} Z_{jkt}^{move} - \sum_{j \in \mathcal{L}} Z_{kjt}^{move} = Z_{kt}^{all}, \forall\, k \in \mathcal{L}, t \in T \setminus \{0, n_t\}$ ... (101)

$\sum_{k \in \mathcal{L}} Z_{jkt}^{move} = Z_{j,t-1}^{all}, \forall j \in \mathcal{L},\ t \in T \setminus \{0, n_t\}$ ... (102)

$\sum_{k \in \mathcal{L}} Z_k^{new} = V^{in}$ ... (103)

$\sum_{k \in \mathcal{L}} Z_k^{leave} = V^{out}$ ... (104)

$Z_k^{leave} \leq Z0_k^{all}, \forall\, k \in \mathcal{L}$ ... (105)

$Z_{kt}^{all} - M * U_k \leq 0\ , \forall k \in \mathcal{P}_d, t \in T \setminus \{n_t\}$ ... (106)

$Z_{kt}^{all} - M * (U_k + Q_k^{open}) \leq 0\ , \forall k \in \mathcal{P}_b, t \in T \setminus \{n_t\}$ ... (107)

$ZZ \geq 0$ ... (non_19)

$\bar{G}_{ikt}^1 \geq 0, \forall\, i \in A,\ k \in \beta_d, t \in T \setminus \{n_t\}$ ... (non_20)

$\tilde{G}_{ikt}^1 \geq 0, \forall\, i \in A,\ k \in \beta_d, t \in T \setminus \{n_t\}$ ... (non_21)

$\bar{G}_{ikt}^2 \geq 0, \forall\, i \in A,\ k \in \beta_d, t \in T \setminus \{n_t\}$ ... (non_22)

$\tilde{G}_{ikt}^2 \geq 0, \forall\, i \in A,\ k \in \beta_d, t \in T \setminus \{n_t\}$ ... (non_23)

$\bar{E}_{ikt} \geq 0, \forall i \in A, k \in \beta_m, t \in T \setminus \{n_t\}$ ... (non_24)

$\tilde{E}_{ikt} \geq 0, \forall i \in A, k \in \beta_m, t \in T \setminus \{n_t\}$ ... (non_25)

$D_{ikt} \geq 0, \forall i \in A, k \in \mathcal{L}, t \in T \setminus \{n_t\}$ ... (non_26)

$Z_{kt}^{all} \geq 0$ and integer, $\forall k \in \mathcal{L}, t \in T \setminus \{n_t\}$ ... (int_16)

$Z_{jkt}^{move} \geq 0$ and integer, $\forall j \in \mathcal{L}, k \in \mathcal{L}, t \in T \setminus \{n_t\}$ ... (int_17)

$Z_k^{new} \geq 0$ and integer, $\forall k \in \mathcal{L}$ ... (int_18)

$Z_k^{leave} \geq 0$ and integer, $\forall k \in \mathcal{L}$ ... (int_19)

$Y_{ikt} = 0$ or $1, \forall i \in A, k \in \beta_d, t \in T \setminus \{n_t\}$ ... (bin_10)

$X_{ikt} = 0$ or $1, \forall i \in A, k \in \beta_m, t \in T \setminus \{n_t\}$ ... (bin_11)

$U_k = 0$ or $1, \forall k \in \delta_d$ ... (bin_12)

$Q_k^{open} = 0$ or $1, \forall k \in \delta_m$ ... (bin_13)

$U_{jk} = 0$ or $1, \forall j \in F_0^{in}, k \in \delta_m$ ... (bin_14)

The constraints in this model can be understood in a way similar to that for previous models. Similar to model III, this model allows relief goods to be distributed from any distribution centre to any disaster area in the whole region. Similar to model I, this model does not consider future information. Different from both models I and III, this model allows vehicle sharing for relief goods distribution and victim evacuation. Therefore, this is an integrated model, rather than two parts (parts a and b). Due to vehicle sharing, the vehicle time requirements are calculated differently, considering both ways in a trip, and possible triangular trips – delivering relief goods from a distribution centre to a disaster area, then evacuating victims from this area to a medical facility at a different site and finally returning to the original distribution centre. This can be seen from constraints (85) and (86).

3.6 Model IV

Similar to models III and II, model IV is proposed to realize the potential for improvement in the presence of a National Board for Disaster Management and its derivatives at several levels. This model is also intended to improve the performance of the 'current-practice' location-allocation model. Model IV accommodates the possibility to jointly evacuate victims and distribute commodity relief and the consideration of future information.

3.6.1 Additional Assumption

Similar to the situation in model III, it is possible in model IV that the departing times of medical facilities (of which arrival times are known in advance) are either not known beforehand or uncertain. In this case, these incoming medical facilities are assumed to be able to stay in the disaster scene during the planning horizon.

It is also highly likely that information on resources changes as time goes on. Examples of changes are numbers of vehicles becoming available at particular times, when and how many incoming medical facilities already considered arrive at and leave the disaster scene, and when and how many other incoming medical facilities will arrive at and depart from the scene. Model IV is therefore re-run every time these changes occur.

3.6.2 Sets in Model IV

Sets used in model IV are exactly the same with the sets appear in model II.

3.6.3 Parameters in Model IV

In addition to parameters defined in previous sections, the following are parameters employed in model IV.

V_t^{in}	Number of new vehicles becoming available at time point t;
V_t^{out}	Number of vehicles leaving the disaster scene at time point t;

3.6.4 Variables in Model IV

Decision variables used in model IV are identical to the decision variables defined and used in model II.

3.6.5 Mathematical Model

Objective function:

Objective expression (80)

Subject to the following constraints:

Constraints (22), (42), (81)-(90), (94)-(96), (98)-(99), (102), (105), (non_9), (non_13)-(non_15), (non_19)-(non_26), (int_16)-(int_17), (bin_10)-(bin_12), and

$\sum_{k \in \delta_m} U_{jk} \leq 1, \forall j \in F_t^{in}, t \in T \backslash \{n_t\}$ ... (110)

$Q_{kt}^{open} \leq \sum_{\tau=0}^{t} \sum_{j \in F_\tau^{in}} U_{jk} - \sum_{\tau=0}^{t} \sum_{j \in F_\tau^{out}} U_{jk}, \forall k \in \delta_m, t \in T \backslash \{n_t\}$ ... (111)

$M * Q_{kt}^{open} \geq \sum_{\tau=0}^{t} \sum_{j \in F_\tau^{in}} U_{jk} - \sum_{\tau=0}^{t} \sum_{j \in F_\tau^{out}} U_{jk}, \forall k \in \delta_m, t \in T \backslash \{n_t\}$ ... (112)

$\sum_{i \in A} X_{ikt} \leq M * Q_{kt}^{open}, \forall k \in \delta_m, t \in T \backslash \{n_t\}$ ... (113)

$Z0_k^{all} + Z_{k0}^{new} - Z_{k0}^{leave} + \sum_{j \in \mathcal{L}} Z_{jk0}^{move} - \sum_{j \in \mathcal{L}} Z_{kj0}^{move} = Z_{k0}^{all}, \forall k \in \mathcal{L}$ ... (114)

$Z_{k,t-1}^{all} + Z_{kt}^{new} - Z_{kt}^{leave} + \sum_{j \in \mathcal{L}} Z_{jkt}^{move} - \sum_{j \in \mathcal{L}} Z_{kjt}^{move} = Z_{kt}^{all}, \forall k \in \mathcal{L}, t \in T \backslash \{0, n_t\}$ ... (115)

$\sum_{k \in \mathcal{L}} Z_{kt}^{new} = V_t^{in}, \forall t \in T \backslash \{n_t\}$ ... (116)

$\sum_{k\in\mathcal{L}} Z_{kt}^{leave} = V_t^{out}, \forall t \in T\backslash\{n_t\}$ ... (117)

$Z_{k0}^{leave} \leq Z0_k^{all}, \forall\, k \in \mathcal{L}$ ... (118)

$Z_{kt}^{leave} \leq Z_{k,t-1}^{all}, \forall\, k \in \mathcal{L}, t \in T\backslash\{0, n_t\}$ ... (119)

$Z_{kt}^{all} - M * Q_{kt}^{open} \leq 0\ , \forall k \in \mathcal{P}_m, t \in T\backslash\{n_t\}$ ... (120)

$Z_{kt}^{all} - M * (U_k + Q_{kt}^{open}) \leq 0\ , \forall k \in \mathcal{P}_b, t \in T\backslash\{n_t\}$ ... (121)

$Z_{kt}^{new} \geq 0$ and integer,$\forall k \in \mathcal{L}, t \in T\backslash\{n_t\}$ ... (int_20)

$Z_{kt}^{leave} \geq 0$ and integer,$\forall k \in \mathcal{L}, t \in T\backslash\{n_t\}$ ... (int_21)

$Q_{kt}^{open} = 0$ or $1, \forall k \in \delta_m, t \in T\backslash\{n_t\}$ ... (bin_15)

Constraints in model IV are very similar to those in model II. The difference is that model IV considers future information on resource availability in the decisions, as can be seen from the constraints explicitly listed above.

CHAPTER 4

ON MODEL TESTING WITH COMPUTATIONAL EXPERIMENTS

In this chapter, the results from computational experimentation of the four models developed in the preceding chapter are presented.

4.1 Justification of the Test Data

Several computational experiments are carried out to test the applicability and performance of the models. In doing so, several factors are taken into account. These include total number of time points, total numbers of disaster areas and sub-regions and maximum possible values of percent deviation of information about future resource availability from its real value.

With regard to the number of time points, the research considers two cases. The first total number of time points taken into consideration is 10 and, along with other factors explained later, represents a small, but realistic problem size allowing the relative merits of the four models to be measured. In the second case, the number is extended to 15. With respect to West Sumatera earthquake, each time period represents one day of disaster management. In fact, the central government declared that the response would last for 2 months (this subsequently was revised as 1 month time periods). However, a 15 day period was adequate to perform the process of evacuation of injured victims to medical facilities. The research, therefore, uses this number of time points.

Total number of sub-regions and total number of disaster areas are other factors considered in the experiments. According to the fieldwork performed by the author, there are 17 sub-districts and 47 nagaris – the latter is a regional unit within a sub-district - in the Padang Pariaman District. This is taken as the second case of the total numbers of sub-regions and disaster areas or, in other words, the 17 sub-districts are used as sub-regions and the 47 nagaris are utilised as disaster areas in this second case of the total numbers of sub-regions and disaster areas. Data representing a smaller case (which from now on is used as the first case of the total numbers of sub-regions and disaster areas) have been created using 3 (hypothetical) sub-regions and 9 (hypothetical) disaster areas, but with the same number of people as in the larger case. Further detail about these two cases can be seen in Table 4.1 and Table 4.2.

Possible maximum value of information deviation on resource availability at the forthcoming time points from its true value is another factor taken into account. Deviation of information reflects the fact that there is likely to be uncertainty/inaccuracy about information with regard to future resource availability. For instance, the number of vehicles available at particular time points, the numbers of incoming medical facilities already considered to arrive at and to leave from the disaster scene at future time points, and the numbers of other incoming medical facilities to arrive at and to depart from the scene may change as time progresses. In this matter, 3 cases are used: absolutely accurate information (i.e. 0% deviation of information), (up to) 5% information deviation, and (up to) 25% deviation of information. In this thesis, “deviation” or “information deviation” or “deviation of information” is frequently, but not always, used to describe this future-resource-availability-related information.

Besides those previously mentioned factors, the computational experiments also include information on several parameter values and sets. Alternative sites either for medical facilities or for distribution centres or for both are examples of sets. Information on injured victims and injured-free sufferers in disaster areas, existing medical facilities, vehicle availability, incoming and outgoing temporary medical facilities, travelling times among sites and penalties for either not evacuating victims or not delivering relief goods is examples of parameter values.

Again, information on the West Sumatera earthquake – especially that related to Padang Pariaman District - that was collected between November 2009 and January 2010 is used as a basis. In cases where the necessary data are not available, they have been generated, details are provided below.

In this research, there are several types of sites. These include existing medical facilities (if any), existing distribution centres (if any), alternative sites for temporary medical facilities and alternative sites for temporary distribution centres. The fieldwork found that, during the earthquake upheaval, a government-owned hospital at provincial level did serve the earthquake victims. With this regard, the research takes this existing hospital into consideration. Locations of distribution centres in each sub-region – in this case, sub-district –, meanwhile, need to be decided immediately after the arrival of the earthquake. Accommodating this situation, the research proposes two alternative sites for a distribution centre in each sub-region. In total, therefore, 34 alternative sites for 17 distribution centres are proposed for the whole region, i.e. the whole district. Out of 24 medical centres in the region at that moment, only a small number were documented by the local authority as being only lightly damaged and able to provide service albeit at a significantly reduced level. The remaining medical centres, on the other hand, were more heavily damaged and, therefore, were only used to store goods. With this regard, the research uses 3 as the total number of alternative sites for temporary medical facilities.

Other sites needed in model II and model IV – that is, existing sites with distribution centres and allowed to have medical facilities, existing sites with medical facilities and allowed to have distribution centres, sites with both distribution centres and medical facilities, alternative sites for temporary distribution centres, alternative sites for temporary medical facilities and alternative sites for both temporary distribution centres and temporary medical facilities - are derived from the sites selected previously. The existing hospital previously mentioned, for example, can stay as it is, i.e. an existing site with medical facilities, or become an existing site with medical facilities and allowed to have a distribution centre.

Precise travel times - among sites and between sites and disaster areas – could not be determined and were generated by using approximate minimum and maximum travel times based on existing places in the Padang Pariaman District.

Data on injured victims and injury-free sufferers also need to be supplied to the models. In the case of 47 disaster areas, the data originate from the population within each sub-district in Padang Pariaman District based on the registration process performed by the Central Agency on Statistics (Indonesian: *Badan Pusat*

Statistik (BPS)), Padang Pariaman District, at the end of year 2008. From this number, data on injured victims within each disaster area – i.e. the nagari - were firstly generated from the data on total population within the same disaster area. The data on injury-free sufferers within each of the disaster areas are subsequently acquired by subtracting these injured victim figures from the total population. The data in these disaster areas are subsequently pooled into 9 new data. These are then used as related data for the case of 9 disaster areas. The total population of each of the disaster area in the case of 47 disaster areas are provided in Table 4.1. Table 4.2, on the other hand, provides the total population in the case of 9 (hypothetical) disaster areas.

Table 4.1 Sub-regions, disaster areas and total population in each disaster area, Padang Pariaman District, West Sumatera (source: BPS (2009))

No.	Sub-region	Disaster areas	Total population in each disaster area (in persons)
1.	Batang Anai	Ketaping	12,205
		Kasang	12,733
		Sungai Buluh	19,266
2.	Lubuk Alung	Lubuk Alung	40,952
3.	Sintuk Toboh Gadang	Toboh Gadang	8,388
		Sintuk	8,167
4.	Ulakan Tapakis	Tapakis	5,901
		Ulakan	14,150
5.	Nan Sabaris	Sunua	6,733
		Padang Bintungan	3,732
		Pauh Kamba	5,796
		Kapalo Koto	1,389
		Kurai Taji	8,725
6.	2 x 11 Enam Lingkung	Lubuk Pandan	5,119
		Sicincin	8,492
		Sungai Asam	3,703
7.	Enam Lingkung	Koto Tinggi	3,434
		Gadua	2,758
		Toboh Ketek	1,685
		Pakandangan	5,295
		Parit Malintang	5,522
8.	2 x 11 Kayu Tanam	Kapalo Hilalang	5,779
		Kayu Tanam	4,953
		Guguk	5,919
		Anduring	7,584
9.	VII Koto Sungai Sarik	Balai Aia	8,548
		Lareh Nan Panjang	3,953
		Lurah Ampalu	6,343
		SeiSarik	14,555
10.	Patamuan	Sungai Durian	4,583
		Tandikat	11,011
11.	Padang Sago	Koto Dalam	4,050
		Batu Kalang	2,335
		Koto Baru	1,933
12.	V Koto Kampung Dalam	Campago	12,235
		Sikucur	10,441
13.	V Koto Timur	Limau Puruik	3,173
		Kudu Gantiang	5,741
		Gunung Padang Alai	5,995
14.	Sungai Limau	Pilubang	13,386
		Kuranji Hilir	15,702
15.	Batang Gasan	Gasan Gadang	5,414
		Malai V Suku	5,926
16.	Sungai Geringging	Kuranji Hulu	21,705
		Malai III Koto	5,613
17.	IV Koto Aur Malintang	III Koto Aur Malintang	14,453
		Malai III Koto	4,772
Total population in all disaster areas (in persons)			390,247

Table 4.2 Sub-regions, disaster areas, and total population in each disaster area in the first case of total numbers of sub-regions and disaster areas

No.	Sub-region	Disaster areas	Total population in each disaster area (in persons)
1.	Sub-region I	Area 1	93,544
		Area 2	38,683
		Area 3	33,224
2.	Sub-region II	Area 4	29,426
		Area 5	51,485
		Area 6	42,005
3.	Sub-region III	Area 7	28,295
		Area 8	48,747
		Area 9	24,838
Total population in all disaster areas (in persons)			390,247

Some medical teams along with relatively complete medical equipment also came to Padang Pariaman District several days after the earthquake arrival (see Table 4.3). These, for instance, originated from centres for regional and sub-regional health crisis response assistance around the affected area. Considering the medical equipment they brought in, the research makes the assumption that the medical teams can serve as temporary medical facilities, which the models are able to deploy to particular sites.

Table 4.3 Arrival and departure of temporary medical teams (source: the fieldwork)

No.	Origin of temporary medical team	Arrival		Departure	
		Date	Time point	Date	Time point
1.	Region I (North Sumatera), Centre of Health Crisis Management, Ministry of Health, Republic of Indonesia	03/10/2009	3	16/10/2009	16
2.		03/10/2009	3	16/10/2009	16
3.		03/10/2009	3	16/10/2009	16
4.		03/10/2009	3	16/10/2009	16
5.		03/10/2009	3	16/10/2009	16
6.	Medecins Sans Frontieres (MSF), Spain	05/10/2009	5	16/10/2009	16

Information on vehicle availability appears in two forms. Information on vehicles for transporting injured victims is obtained from the Ministry of Health Affairs, Padang Pariaman District (see Table 4.4). Information on vehicles for distributing relief, on the other hand, cannot be acquired from any sources and therefore needs to be generated. Concerning the fact that a sub-region in Padang Pariaman District is relatively small, it is assumed that, at a certain time point, the maximum possible number of vehicles for distributing relief coming from other areas is 1. Using this value as an upper limit and 0 as a lower limit, the numbers of vehicles for relief distribution in each sub-region coming from other areas at a certain time point is then generated by using a uniform distribution.

Table 4.4 Vehicles for transporting injured victims
(source: the Ministry of Health Affairs, Padang Pariaman District)

Time point	Date	Total number of arriving and departing vehicles	
		Total arrival	Total departure
0	30/09/2009	24	0
1	01/10/2009	1	0
2	02/10/2009	3	0
3	03/10/2009	24	0
4	04/10/2009	11	0
5	05/10/2009	25	0
6	06/10/2009	19	2
7	07/10/2009	5	1
8	08/10/2009	8	3
9	09/10/2009	4	10
10	10/10/2009	2	1
11	11/10/2009	2	2
12	12/10/2009	5	1
13	13/10/2009	4	2
14	14/10/2009	2	1
15	15/10/2009	1	8

In performing the process of distributing relief and transporting victims, it is very highly likely that not all in need can be served immediately. In both cases of delay, the models impose particular penalties. Recognising the high importance of human life saving, the research takes a position that not evacuating victims sensibly should be penalised more heavily than not delivering relief supplies on time. In particular, the penalty value for not evacuating injured victims on time is uniformly generated from the value range of 10 to 20 whereas the penalty for shortages of once-for-all goods or repeatedly-needed commodities is uniformly generated from the value range of 1 to 10.

For the rest of the thesis, the following symbols are applied to represent those factors and problems. The total number of time points is represented by NT followed by the number of time points plus 1 (to represent the initial time point 0). For example, NT11 stands for 10 time points. The numbers of sub-regions and disasters areas, meanwhile, are signified by R and Na followed by the numbers of sub-regions and disaster areas. Three sub-regions and nine disaster areas, for instance, are presented as R3Na9. Finally, maximum values of percent deviation of information on future resource availability appear as themselves. With this regard, 5% stands for five percent deviation of information on future resource availability. Therefore, NT11R3Na9_5% should be read as follows: this is a problem with 10 time points, 3 sub-regions and 9 disaster areas, and the information on future resource availability may deviate up to 5% from its real value.

Combining all of the abovementioned factors and symbols, 12 combinations of problem sizes are subsequently obtained. For each problem size, the first 10 uniformly generated data sets – including the aforementioned generated data such as sites, travel times between sites, number of injured victims and injury-free sufferers in disaster areas, vehicle availability, incoming and outgoing temporary medical facilities and penalty values – are obtained and used in the research. Computational experiments using Xpress MP Software are subsequently performed on all these problem instances.

When a model is used to solve a problem instance in the computational experiments, the model is formulated and solved for each decision time point. For the R3Na9 problems, the solution time of the model at each time point is limited up to 1200 seconds. Because models III and I consist of two sub-models, this means that the time limit for solving the sub-models IIIa, IIIb and Ib at each time point is set to 600 seconds. For sub-model Ia, the time restriction for each sub-region is 600 seconds divided by the number of sub-regions. In terms of Xpress MP Software, this means that XPRS_MAXTIME, a control parameter in Xpress optimizer, is put in place.

Problems R17Na47, in the meantime, have much bigger numbers of decision variables and, therefore, much higher dimensions of solution spaces. As a consequence, time required to reach an integer solution is much longer. It is also a matter of fact, however, that the size of model decreases at each successive time point. With this respect, the computational experiments for R17Na47 problems are carried out by allowing a much longer time limit for the first time point. This limit is decreased for each successive time point. The same idea is used for the maximum time allocated to the cutting process (i.e. by setting up XPRS_MAXCUTTIME, another control parameter in Xpress optimizer). More specifically, XPRS_MAXTIME and XPRS_MAXCUTTIME are set to 5400 – 600*T and 600 – 60*T for models II and IV, 2700 – 300*T and 300-30*T for sub-models Ib, IIIa and IIIb, and (2700 – 300*T)/ R and (300 – 30*T)/ R for sub-model Ia, where T stands for decision time point and R represents the number of sub-regions.

Another stopping criterion taken into consideration is related to the objective function of the mixed integer problems under concern. In this case, another control parameter in Xpress optimizer, XPRS_MIPRELSTOP, is set in place at a value of 0.05. This means that the global search will stop if a mixed integer solution has been found within 5% of the best bound of the optimum solution.

The summary of all 12 problem sizes and their symbols can be seen in Table 4.5. A short explanation about the table is provided afterwards.

Table 4.5 Summary of the problem sizes in computational experiments

No.	Problem size notation	No. time points	No. sub-regions	No. disaster areas	Maximum % deviation
1.	NT11R3Na9_0%	10	3	9	0
2.	NT11R3Na9_5%	10	3	9	5
3.	NT11R3Na9_25%	10	3	9	25
4.	NT16R3Na9_0%	15	3	9	0
5.	NT16R3Na9_5%	15	3	9	5
6.	NT16R3Na9_25%	15	3	9	25
7.	NT11R17Na47_0%	10	17	47	0
8.	NT11R17Na47_5%	10	17	47	5
9.	NT11R17Na47_25%	10	17	47	25
10.	NT16R17Na47_0%	15	17	47	0
11.	NT16R17Na47_5%	15	17	47	5
12.	NT16R17Na47_25%	15	17	47	25

The introduction of total number of disaster areas (and sub-regions) and total number of time points determine the total number of decision variables and, ultimately, the size of the problems. With this regard, it is clear that NT11R3Na9_0% has much fewer decision variables than NT16R17Na47_0%. Concerning model IV with $\mathcal{D}_o$=0, $\mathcal{M}_o$=1, $\mathcal{D}$=0, $\mathcal{M}$=0, $\mathcal{B}$=0, $\mathcal{P}_d$=34, $\mathcal{P}_m$=3 and $\mathcal{P}_b$=0, for instance, the total number of decision variables in NT11R3Na9_0% (35,840) is only around one fifth of the total number of decision variables in NT16R17Na47_0% (181,481). Regarding the fact that the mixed integer programming problems are *NP*-hard, the former problem size is much easier to solve and the second problem size needs much longer time to find its optimum solution. The deviation of information on future resource availability, on the other hand, will affect the accuracy of input to the models. It is hypothesised that the more accurate the information on resource availability, the better the outcome of the models will be.

Section 4.2 presents output data from the computational experiments. Processed experimental data are provided in Section 4.3. The results of the experiments are further discussed and analysed, of which details are provided in Appendix E and of which summary is presented in Section 4.3.

4.2 Raw Data from Computational Experiments

As already mentioned, 10 data sets were generated for each of the 12 problem sizes and the results from these experiments are provided in the tables in Appendix A.

During the process of solving each problem instance, accumulated objective values (maximum sufferings) up to each decision time point are produced. The accumulated objective values at the end of the planning horizon are presented in the 12 tables in Appendix A as the accumulated objective values, together with associated values for the average and standard deviation. These two descriptive statistics are calculated in aiding the analysis and discussion in the upcoming section.

It is necessary to note that the results of model I and model II are not affected by the future information deviation (i.e. 0%, 5% or 25%). The objective value of model I for NT11R3Na9_0% data set 1, for instance, is 27,496,072.739924. This value is exactly the same as those forNT11R3Na9_5% data set 1 and NT11R3Na9_25% data set 1.This is because both model I and model II are run with resources that are available at the decision time point of the running process and, as a result, there is no need to take information on resource availability at the upcoming time points into account.

4.3 Analysis and Discussion

A research problem has been identified and presented in Chapter 1. Following the problem, four different mathematical models have already been constructed. Each of the models includes a variety of decision variables and parameters. Many of the parameters have a large number of possible values. These lead to a very large number of combinations of inputs for the models. By considering this fact, 10 different inputs are chosen from within each problem size. In other words, computational experimentation for the model testing is performed by using 10 samples, with each sample data set applied to each of the four models.

As already mentioned, the computational experiments are intended to get insight about the performance of the models. The insight can be from a statistical point of view such that, statistically speaking, it can be inferred whether a particular model performs better than other models. This is what is called statistical significance of the results. A short note about tests of statistical significance employed in the thesis is provided in Appendix B. A brief overview on tests on assumptions of residuals of the original data and summary of the test results on the data are provided in Appendix C.

An additional issue addressed in the analysis and discussion is the practical meaning, practical significance or usefulness of research results (for an advocacy that the usefulness of the research results should be examined, see e.g. Kirk (2007) and Hayat (2010)). With this motivation, effect sizes of the study are calculated and provided. The analysis and discussion are also carried out by taking the context of the study into account.

Effect size (or ES in short) refers to the extent or strength of research results (Durlak, 2009) or, in other words, ES is the effect of a particular treatment on the result of research interest or the relationship between research variables (Berben *et al.*, 2012). ES is a statistic that measures the magnitude to which sample statistics deviate from the null hypothesis (Thompson, 2006). A rule of thumb is that ESs of around 0.2 are small in size, those approximately 0.5 are medium, and those roughly or larger than 0.8 are of large magnitude (see, for example, Cohen (1992) and Durlak (2009)). Following Kirk (2007), a small effect size is one for which 58% of resulted outputs with regard to a certain treatment exceed outputs with respect to the other treatment, a medium effect size is one for which 69% of resulted outputs concerning a certain treatment exceed outputs with regard to the other treatment, and a certain treatment of which 89% of its output exceeds the other treatment's outputs has a large effect size. The formula for calculating the effect size in the current research thesis is provided in Appendix B.

The contextualisation of the research is another practical significance issue of the current research (see, for instance, Buhi (2005) on contextualisation of study). For the purposes of this thesis, a measure referred to as suffering reduction is calculated. Firstly, relative differences between objective values of different models are calculated. Secondly, the relative difference is multiplied by the total number of victims in Padang Pariaman District as a result of West Sumatera earthquake. The average and standard deviation of suffering reduction are also calculated. Calculation results of the suffering reduction concerning the original data are provided in Appendix D.

4.3.1 Comparing Model Performance

By mainly taking statistical significance and practical significance points of view, the raw output data from computational experiments are subsequently analysed and discussed. Detailed analysis and discussion on model performance is provided in Appendix E.1.

In general, several insights with regard to model performance for the problem sizes under concern can be summarised as follows. Firstly, model I performance is surpassed by all other models in all problem sizes. Secondly, model II and model IV perform better than model III on R3Na9 problems. Thirdly, contrary to the second summary, model III performance goes beyond those of model II and model IV on NT16R17Na47 problems. Fourthly, all of model II, model III and model IV perform roughly equally on NT11R17Na47 problems. Fifthly, the performances of model IV and model II are mostly very similar over problem sizes.

Theoretically, it was expected that all the proposed models – i.e. model II, model III and model IV – would improve the relief distribution and victim evacuation in comparison with model I. It was also expected that model IV would perform the best amongst the four models over any problem size. Contrasting the performance of the four models between the theoretical patterns – as summarised above - and the real patterns – as summarised in the preceding paragraph - it is apparent that the real patterns represented by insight number one and number two do match the theoretical patterns. Insights three, four and five, meanwhile, show that the related real patterns do not follow the related theoretical patterns. This leads to the need to look further into the overall results of the computational experiments and contrast them to both theoretical ideas and the way the computational experiments are performed, a matter which will be addressed in Sub-section 4.3.3.

4.3.2 Comparison of the Impact of Information Deviation

In addition to the tests on model performance for a variety of problems, tests and calculations that solely examine the impact of information deviation on model performance are also conducted. The tests and calculations are eventually analysed and discussed, of which details are presented in Appendix E.2.

General insights on the effect of information deviation to problems under concern follow. Firstly, the tests confirm that information deviation under study does not affect model III performance for any of the problems under concern. Secondly, model IV with exactly accurate information performs the best among all alternatives only in the case of NT16R3Na9_0% over NT16R3Na9_25% and in the NT11R17Na47 problems.

Theoretically speaking, it is anticipated that model inputs with more accurate future resource availability should make the model perform better than the inputs with less accurate values. Computational experiments performed so far, unfortunately, do not always support this premise. A further look, therefore, is needed and is provided in the next sub-section.

4.3.3 A Further Look

From all analyses and discussions in this chapter so far, it is obvious that all the proposed models are able to improve the process of delivering relief to the victims and transporting injured victims from the disaster areas in comparison with model I, both statistically and practically. It is also evident that, from a practical point of view, model II and model IV surpass model III in performing relief distribution and injured victim transportation for small problem sizes. With regard to the effect of information deviation on future resource availability, it is advised that model IV with 100% accurate information has a better performance over all of the other choices of delivering the relief and transporting the injured victims in case of NT16R3Na9_25% and NT16R3Na9_0% problems and in NT11R17Na47 problems. These match what is expected from the results of the computational experiments.

The experiments, nonetheless, suggest that, practically, model II and model IV conduct the process of relief distribution-victim evacuation worse than model III for large problem sizes. It is also found that the model inputs with perfectly accurate future information on resource availability do not always make the related model carry out the process of minimising the unmet demands better than those with inaccurate information.

As mentioned previously, the complexity of the models increases from model I either by including information on resource availability in the future into the model(s) or by combining the relief distribution and the victim evacuation or both. As a consequence, the total number of variables in the models becomes larger than that in the model I. For 15 time points, the pattern of the total number of variables in the four models, in ascending order, is model I, model III, model II and model IV. This makes the solution spaces created by the implementation of the four models with regard to a particular set of inputs also become larger from model I to model IV, following the pattern of the total number of variables of each of the models. By allowing exactly the same time for all models, it is extremely likely that with time limits, the percentage of the solution space that can be explored for larger models will be far smaller than that for smaller models, leading to a likely degradation in terms of progress towards finding an optimal solution. This is confirmed by the experiments, wherein model I in most of problems under concern and model III in most of the small problems (i.e. R3Na9) need less than the time allowed to complete the running process for one time period, whilst execution of model II and model IV had to be terminated prematurely before completion of the running process for the same time period in all problems. Taking the fact that the total number of variables in model IV with regard to a particular problem is always greater than that in model II with respect to the same problem, it is likely that the solution resulting from the implementation of model IV will be farther from optimality in comparison with the distance between the solution given by model II and its optimum value.

Another issue worthy of discussion is the indication that information accuracy on future resource availability does not always guarantee a better result. The matter of the size of solution spaces – discussed above – is also likely to be relevant in this case. Another possibility is the effect of using a 5% cutoff in the branch-and-bound search, especially to those experiments relating to model I in all problem sizes and to model III in small problem sizes. Less than the maximum time allowed is needed by models I and III to complete the computational process for one period. Because of the presence of the cutoff, the solutions obtained from the previously mentioned computations may never reach optimality. This most likely explain why more accurate information on resource availability at the upcoming time points does not always make a model perform better than less accurate information.

The next chapter presents research designed to cope with the problem of large solution spaces. The issue of information accuracy, for the reasons of its narrower scope of impact, on the other hand, is put aside and left for future research.

In general, the idea of the research presented in the next chapter is to make the solution spaces smaller in order for the application of the proposed models – especially model II and model IV – to give better solutions contrary to the solutions resulted from the application of model I and model III. So-called heuristic approaches are proposed and tested with computational experiments. The heuristics along with their experimental results are subsequently analysed and discussed.

CHAPTER 5
ON HEURISTICS

This chapter focuses on heuristics applied to the problems under study. In the chapter, a general introduction is presented first. Subsequently, an idea on how the solution spaces can be reduced is presented. The three ways to reduce the solution spaces applied in the research – including computational experiments that follow - are provided in the section after. The present chapter concludes with a summary of findings.

5.1 Introduction

In the previous chapter, it was argued that a potential reason for the relative performance of the four models not following the expected pattern might be the increase in solution space for models II, III and IV causing the solutions obtained at the end of the time limit to be far from optimal. It is hoped that by reducing the size of the solution space, and thereby allowing later models to explore the solution space more fully in the time allowed, the expected improvement of model IV and model II in comparison with model I and model III will be realised. It is also expected that, with the application of the heuristics, the performance of model IV will prove to be better than the performance of model II.

5.2 On How to Reduce Solution Spaces

Regarding the result of computational experiments with 15 time points, 47 disaster areas, 17 sub-regions, and 0% deviation of information about resource availability in the upcoming time periods, it seems that all the proposed models perform much better than model I. It is nonetheless apparent that model III outperforms model II and model IV. This is not in line with the result of previous computational experiments on smaller problems.

One of the possible causes of this result is the conjecture that the total numbers of decision variables in model II and model IV are much larger than those in model I and model III. This leads to larger solution spaces. With limited running time for each time point of model II and model IV, the obtained solutions are still very far from the optimum values. It might therefore be valuable to reduce the solution spaces. This can be done in many ways of which three are (1) reducing time points, (2) merging the total number of temporary distribution centres that have to be built into a smaller number, and (3) combining (1) and (2).

The rest of this section briefly describes these three heuristic approaches. Time point reduction is presented first in Sub-section 5.2.1. Sub-section 5.2.2 deals with the pooling of distribution centres. Time point reduction in combination with pooling of distribution centres is presented in Sub-section 5.2.3. The problems with 15 time points, 47 disaster areas, 17 sub-regions and zero percent deviation of information on future resource availability (NT16R17Na47_0% or the 0% problem in short) are used to test the various heuristic approaches.

5.2.1 Time Point Reduction

In this heuristic, the number of original time points is reduced. This reduction is realised in three ways, which are explained in the following paragraphs.

The first way addresses the original problem by reducing the number of time points in such a way that the reduced time points are evenly spaced. The original time points are merged into the closest reduced time point. The time point reduction is performed at the very beginning of the problem solving process and these reduced time points are kept unchanged during the solving process.

With respect to the 0% problem, the time points are reduced to 5 time points. The new time points are actually time points 0, 3, 6, 9, 12 and 15 in the original time point set. As a consequence, all related information with regard to resources is also updated. These 5 time points are subsequently treated as time points 0, 1, 2, 3, 4 and 5 in the set of new time points. Please see Figure 5.1below.This heuristic will be referred to as redtime heuristic.

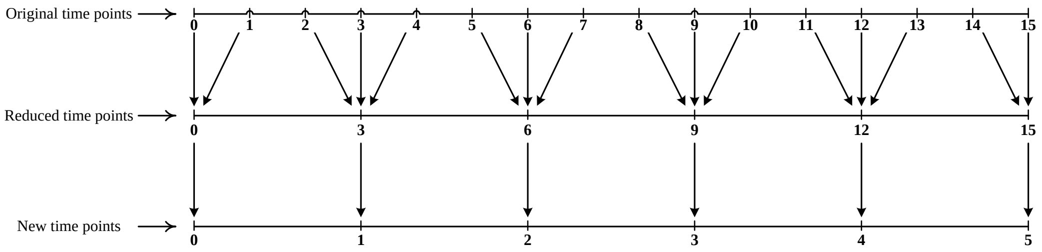


Figure 5.1 Time point reduction, redtime heuristic

The updated information about resources leads to a new composition of resource availability. This sometimes leads to infeasibility. For example, the total number of vehicles leaving the disaster scene at a certain time point may be more than the number of vehicles actually available in sites at the same time point. In this case, the difference between these two numbers of vehicles at the time point is calculated. The number of vehicles resulting from this calculation is subsequently assumed to leave the disaster scene at the next time point.

It is also apparent that the new time points of 0, 1, 2, 3, 4 and 5 are actually time points 0, 3, 6, 9, 12 and 15. Due to this fact, penalty functions for not sending relief distribution and not evacuating victims in a timely fashion, which involve the time duration of suffering, need to be adjusted as well. For example, if the number of periods in the original model is 15 and this becomes 5 after reduction, then one period in the reduced model represents 3 periods in the original time scale. Therefore, the coefficients of the S and W variables in the objective functions and constraints (1), (21), (41) and (81) in the reduced models need to be multiplied by 3, in order to reflect the real objective value.

A computational experiment using this heuristic approach was applied to the 0% problem. The results are presented in Table F.1 of Appendix F along with the average and standard deviation values.

The second time point reduction heuristic differs from the first in that the number of time points is reduced dynamically. In the process of reducing time points, the present time point and the next time point as well as information on resource availability at these two time points are kept unchanged. The period between these first two time points will remain as one time unit. The future time points, on the other hand, change based on how far they are from the present time. The reduction of these later time points is performed by making the assumption that the further a time point is from the present point, the less accurate the related information is likely to be, and so the information needs to be considered in less detail. Under this assumption, therefore, the further ahead the time is from the present time, the longer the period between two adjacent new time points would be in the reduced model. The duration of each period is made one time unit longer than that of the previous period, or the same as the previous time period in cases where it is not possible to keep the period length increasing in the planning horizon. The process of reducing time points and updating related information is performed over the original time points. When applying the model in a rolling horizon fashion, time point reduction and information updating are performed every time there is a need to re-run the model. As in the first heuristic, the coefficients of the *S* and *W* variables in the objective functions and constraints (1), (21), (41) and (81) in the reduced models need to be multiplied by the corresponding period lengths.

Figure 5.2 presents the abovementioned idea with respect to the time points in the 0% problem. Table F.2 of Appendix F presents results of computational experiments performed using this approach and is henceforth referred to as redtime_up.

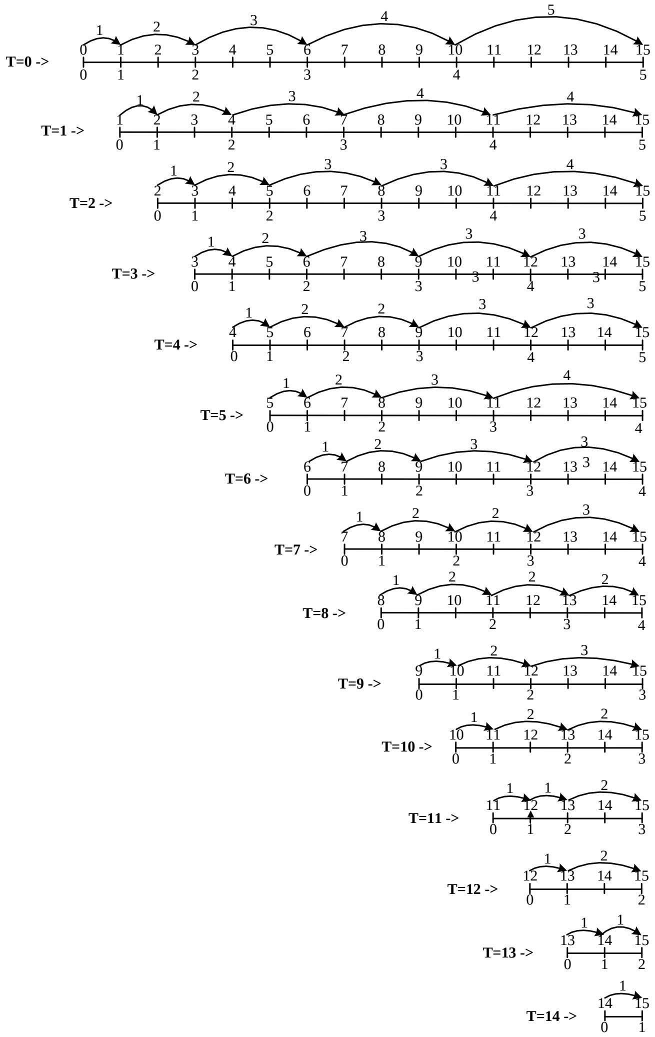


Figure 5.2 Time point reduction, redtime_up heuristic

As can be seen from Figure 5.2, in the reduced model at the decision time point 0 (T=0), the length of the period between the present and the next time point is one time unit, and the lengths of the following periods are 2, 3, 4, and 5, respectively. In the reduced model at the decision time point 1 (T=1), on the other hand, the lengths of the periods are 1, 2, 3, 4 and 4, respectively. In other words, the lengths of the last two periods are the same. It is also clear from Figure 5.2 that the length of each period is always one time unit longer than or the same as that of the previous period.

The third time point reduction heuristic always keeps the next four time points and their related information separate for as long as possible. The remaining time points (and related information on resource availability) are aggregated into the last time point. In this way, it is implied that information on resource availability at the fifth time point onwards is considered to be liable to a degree of doubt. Taking into account information about the first four time points as is, in the meantime, signifies the idea that more recent information is far more likely to prove reliable. This follows the idea on the criticality of a particular disaster during the early period of its onset suggested by, for example, Sheu (2007a, 2007b, 2010), Salmeron and Apte (2010) and Zeimpekis *et al.* (2013) and implied by, for instance, Ginzburg *et al.* (2010).

Figure 5.3 below presents the abovementioned idea with respect to the 15 time points in the 0% problem. Computational experiments with respect to the 0% problem using the notion presented above concerning 10 datasets are carried out, and the results are presented in Table F.3 of Appendix F. This heuristic is henceforth referred to as 4time.

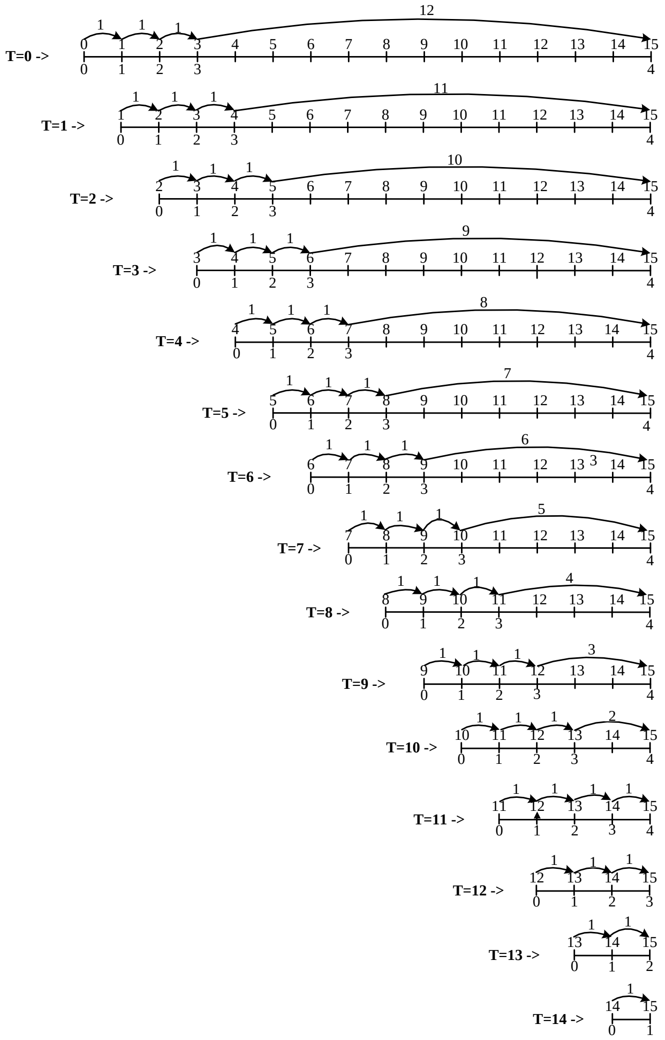


Figure 5.3 Time point reduction, 4time heuristic

5.2.2 Merging Temporary Distribution Centres

As previously mentioned, model I tries to reflect, in many ways, the relief distribution and victim evacuation which took place in the Padang Pariaman District following the 30th September 2009 earthquake. It addresses the relief distribution and victim evacuation separately. The relief distribution is performed separately within each sub-region, and sub-model Ia is concerned with the determination of temporary distribution centre location within the sub-regions and the allocation of disaster areas in the sub-region to the distribution centre. The victim evacuation, on the other hand, is performed for the whole district.

Models II, III and IV are built as an improvement to model I. The later models use the same approach in terms of establishing the exact number of temporary distribution centre locations as in model I. If, for instance, there are 17 sub-regions in model I and each sub-region sets up one temporary distribution centre, then there will be 17 temporary distribution centres in total. The locations of these 17 temporary distribution centres are determined in each of the models II, III and IV and, as a result, there will be 17 temporary centres serving the victims in the disaster areas.

Models II, III and IV, meanwhile, are proposed with an assumption that there is a particular agency which can serve as a command body during the response phase of disaster management. Considering this and taking the case of the 17 sub-regions mentioned in the prior paragraph into account, it seems to make sense to build only one temporary distribution centre instead of 17. By having to determine the location of only one temporary distribution centre, it is expected that the response could be given in a much more coordinated way. In terms of model issues, this is expected to lead to reduced solution spaces. Ultimately, the reduced temporary distribution centres are expected to lead to a more sensible performance of the models.

Results of the application of this heuristic (henceforth referred to as redNdc) to the 0% problem are presented in Table F.4 of Appendix F.

So far, computational experiments are performed by considering the arrivals of a particular number of temporary medical facilities at different time points. In this research, all medical facilities (either permanent or temporary) are assumed to have unlimited capacity to give service. Considering this assumption, it is therefore possible to deploy all these temporary medical facilities to different sites. At the same time, sites with a distribution centre and temporary medical facility are possible to establish in models II and IV. In this respect, it may be worthwhile to establish the number of distribution centres to be exactly the same as the number of temporary medical facilities available to deploy. The second part of experimentation in this category is carried out by using this second proposal of distribution centre pooling as a base.

Table F.5 of Appendix F presents the results of the computational experiments based on the abovementioned idea on the 0% problem. The heuristic is henceforth referred to as redNdc6, where the number 6 refers to the number of temporary medical facilities available to deploy during 15 days of disaster response in Padang Pariaman District after the West Sumatera earthquake.

5.2.3 Time Point Reduction and Distribution Centre Pooling

In this section, the idea is to explore whether combining the time point reduction and distribution centre pooling approaches might be worthwhile.

By using this idea as a foundation, a computational experiment comprising the 10 data sets for the 0% problem is carried out and the results are presented in Table F.6 of Appendix F. Rather than explore all 6 potential heuristic combinations, it was decided to focus on combining 4time together with redNdc6. The combined heuristic is referred as redcomb from this point forward.

5.3 Analysis and Discussion

The analysis and discussion, similar to that in Chapter 4, is conducted from a statistical point of view as well as a practical one. Prior to the analysis, certain inferential statistical tests are employed and particular calculations are performed.

In the first part of the analysis and discussion, results of the computational experiments with regard to the application of heuristics are analysed and discussed. Prior to the analysis, assumptions on residuals of the experimental data are tested and inferential statistical tests appropriate for the data are then employed; effect sizes of models within the heuristics are calculated, and the victim suffering reduction when applying a certain model over the other models using the heuristics proposed in the thesis are calculated. The result of the assumption tests on residuals with regard to the heuristics is summarised and provided in Table G.1 of Appendix G of the thesis; results from Kruskal-Wallis test, an inferential statistics, applied to heuristics-related data are given in Table J.1 of Appendix J; Table J.2 to Table J.7 of Appendix J present Mann-Whitney's (MW's) *P*, effect size (ES) and suffering reduction (SR) average and standard deviation values obtained from related tests; and Table H.1 to Table H.6 of Appendix H of the thesis provide all results for the SR figures (average and standard deviation values are summarised in Tables J.2 to J.7 of Appendix J). Particular values of suffering reduction resulting from the application of certain heuristics are presented in Figures J.1 to J.4 of Appendix J, and are mainly intended to aid the analysis and discussion.

The second part of the analysis deals with the sole performance of each of the models for each of the heuristic approaches. As already mentioned in the final part of Chapter 4 as well as at the beginning of the current chapter, all heuristics in the present chapter are proposed to improve the performance of model IV and model II relative to their performance on the 0% problem and in comparison to the performance of model I and model III. In particular, the heuristics are introduced to give evidence on the idea that model IV is anticipated to give better results than model II. In addition, the second part deals with insights about the performance of the heuristics with regard to a particular model. With this respect, required statistical tests are performed and particular ES values as well as the SR of each of the models compared with others are calculated. Test results on assumption of residuals related to this matter are provided in Table G.2 of Appendix G. Kruskal-Wallis test results of the related data, in the meantime, are provided in Tables J.8–J.11 of Appendix J. Tables J.12–J.15 of Appendix J, meanwhile, present MW's *P*, ES figures, and SR average and standard deviation values. The complete SR figures can be found in Tables I.1.1–I.4.4 of Appendix I.

Lastly, analysis is included which takes a further look at the performance of all four models over all approaches with a view to testing the hypothesis that, theoretically, model IV is expected to perform the best among the four models presented in the thesis.

5.3.1 Model Performance with Proposed Heuristics

Detailed analysis and discussion on model performance with the proposed heuristics is provided in Appendix J.1. The findings can be summarised as follows. Firstly, models II, III and IV perform better than model I both statistically and practically for redtime heuristic. Secondly, the performance of models II, III and IV for redtime_up is better than that of model I; model II performs relatively the same as model III does; and model IV performs better than model III does. Thirdly, for 4time, model I is outperformed by models II, III and IV; model II and model IV, in the meantime, have relatively equal performances for the heuristic. Fourthly, model III, for the redNdc heuristic, performs worse than models II and IV. For redNdc6, model IV performs better than model III, model II and model IV have relatively the same performance and model I performs the worst among the four models. Lastly, models II, III and IV perform much better than model I for the redcomb and, still for the same heuristic, models II and IV perform better than model III does.

5.3.2 Performance of the Heuristic Approaches for Each Model

Besides model performance for particular heuristic approach, performance of the heuristic approaches for each model is also analyzed and discussed. Detailed analysis and discussion on this matter is provided in Appendix J.2.

In summary, the performance of the heuristics is as follows. Firstly, model I is best approached with redtime. Secondly, redcomb performs the best for model II and model IV. Lastly, there is no clear indication about which approach performs the best for model III.

5.3.3 A Further Observation on Model Performance

From the analysis and discussion on model performance with heuristics and individual model performance across various approaches, it is clear that model I performance is dominated by the other three models consistently no matter which heuristic is used to solve the models. This insight matches the insight regarding model I within most problem sizes presented and discussed in Chapter 4.

The results of each individual model solved by different approaches also show that the relative performance of solution approaches is different for different models. This means that the comparative results of the models are dependent on the approaches used if the same approach applies to all models. It will be more meaningful, therefore, to compare the performance of the models by solving each model with the approach most favourable to this model.

From discussion and analysis in Sub-section 5.3.2, it is clear that model I is best approached with redtime (see Sub-section J.2.1 of Appendix J) and redcomb performs the best for model II (see Sub-section J.2.2 of Appendix J) and model IV (see Sub-section J.2.4 of Appendix J). Despite no clear indication about which approach performs the best for model III (see Sub-section J.2.3 of Appendix J), it can be seen from Table J.14 that using redtime makes model III produce higher ES values relative to other approaches. For this reason, redtime is chosen as the best approach for model III. Based on the above choice of best approach for solving each model, assumption tests on residuals were performed and ES values and SR figures of a certain model relative to other models were calculated. The test results on the residuals are provided in Figure K.1 of Appendix K, the calculated ES values and SR averages and standard deviations are presented in Table 5.2 and Tables L.1-L.2 of Appendix L provide the calculated SR figures.

Concerning the test results on residuals, Kruskal-Wallis tests were subsequently performed on the performance of models using their best approach (see Table 5.1). Regarding the very small *P* value in the table (i.e. 0.000), it can be statistically deduced that at least one model performs differently from the others. It is obvious from the figures in the middle columns of the table that model I performs worse than the other models. This is no surprise as all previous analysis has consistently confirmed this.

Table 5.1 Kruskal-Wallis test results with regard to best approach for each model

Model_Approach	Average rank	Median	*P* value
model_I_redtime	35.5	3,497,576	0.000
model_III_redtime	20.6	1,877,467	
model_II_redcomb	14.9	1,293,989	
model_II_redcomb	11.0	1,132,649	

To make pairwise comparisons between the model results obtained by their respective best approaches, a series of Mann-Whitney (MW) tests are conducted. MW’s *P* values of these tests are presented in Table 5.2.

Table 5.2 Values of MW’s *P*, ES, and SR average and standard deviation of the results of the best approach for each model

Relative to approach …	Value of …	With respect to approach …		
		model_III_ redtime	model_II_ redcomb	model_IV_ redcomb
model_I_ redtime	MW’s *P*	0.0002	0.0002	0.0002
	ES	1.40	1.59	1.66
	SR Average	223,695	276,370	283,569
	SR StdDev	99,873	44,016	53,188
model_III_ redtime	MW’s *P*		0.1212	0.0257
	ES		0.82	1.29
	SR Average		69,421	108,996
	SR StdDev		115,645	112,429
model_II_ redcomb	MW’s *P*			0.2730
	ES			0.53
	SR Average			31,423
	SR StdDev			115,460

From the Table 5.2, performances of the models can be compared and, in turn, the research questions about the benefits of coordinating relief distribution and victim evacuation and of considering information on future research availability can be answered.

The *P* values comparing models I and II and comparing models III and IV are small and the corresponding ES values are large. These indicate that coordinating the operations by sharing vehicles for relief distribution and victim evacuation significantly improves the performance as compared to conducting the two operations separately.

Comparing models I and III, the small *P* value and large ES value demonstrate the significant benefit of considering information on future resource availability in the case where relief distribution and victim evacuation are conducted separately. The *P* value comparing models II and IV does not show statistically significant difference between the two models. This might be because after the improvement by coordinating the two operations, the results of model II have less room for further improvement. Nevertheless, a medium ES value does show a certain advantage of model IV over model II. Combining the results of the above two pairwise comparisons, it can be concluded that considering information on future resource availability is beneficial.

In summary, the results in this chapter show that the heuristics are effective in improving solution quality. Comparing the best solutions of the models obtained using their respective most favourable solution approaches, the benefits of coordinating relief distribution and victim evacuation and of considering information on future research availability become clear. Overall model IV performs the best. These are all in line with the conclusions from the small problem results in the previous chapter.

CHAPTER 6
CONCLUSIONS

This final chapter presents overall conclusions, highlights limitations of the current research and considers future research directions in the area of the current research.

6.1 Research Conclusions

In order to deal with the problems of distributing relief, evacuating injured victims, and determining temporary sites following a sudden-onset, difficult-to-predict natural disaster occurrence identified in the current research, four different mathematical location-allocation models are developed. The four models try to minimise the worst suffering of victims as well as total suffering over all disaster areas. Following model testing, analysis and discussion of results, several conclusions can be made:

Conclusion 1: Models II-IV improve on current practice (model I)

Contrasting the performance of model I to models II, III and IV, it is apparent that the last three models perform better in almost all of the problem sizes under concern. In other words, conducting relief distribution and victim evacuation after a sudden-onset, difficult-to-predict natural disaster by using shared vehicles and/or by taking future information on resource availability into account is proven to improve the "current practice".

Conclusion 2: Sharing vehicles is a good approach for small problems

In terms of small problem sizes – i.e. those in which numbers of sub-regions and disaster areas are 3 and 9, respectively - model II and model IV perform better than model III. To put it in another way, the relief distribution and victim evacuation for small problem sizes is better performed by using shared vehicles or concurrently using shared vehicles and taking future information on resource availability into account rather than only taking into consideration future information on resource availability.

Conclusion 3: Taking account of future information works well for larger problems

Combining relief distribution and victim evacuation using shared vehicles, models II and IV are much more complex and more difficult to solve than model III. With limited computation time as set in our experiment, in contrast to the previous conclusion, model III performance goes beyond those of model II and model IV for large problems where time points, number of sub-regions, and number of disaster areas are 15, 17 and 47, respectively. In other words, for these large problem sizes, better solutions can be found with the relief distribution and victim evacuation performed by only taking into consideration future information on resource availability rather than either by using shared vehicles or by simultaneously taking into account future information on resource availability and using shared vehicles.

Conclusion 4: Model II works best in combination with the redcomb heuristic

With respect to Model II, of all the heuristics developed in the current research, it can be concluded that the redcomb heuristic is the best. In other words, the process of distributing relief and evacuating injured victims by using the same vehicles for both activities and all resources available at hand is best carried out by, as long as possible, considering 5 time points only, where the fifth time point aggregates all information on resource availability beyond the four most current time points.

Conclusion 5: Model III is adversely affected by the redNdc heuristic

Model III's performance in combination with the redNdc heuristic in conducting the relief distribution and victim evacuation is the worst. In other words, the idea of squeezing the total number of distribution centres to establish from 17 down to only 1 does not work for this model.

Conclusion 6: Model IV works best in combination with the redcomb heuristic

Similarly to conclusion 4, the redcomb heuristic leads to the best performance for model IV relative to all other approaches. In other words, carrying out the relief distribution and victim evacuation by using the same vehicles and taking into account future information on resource availability for these activities is best done by taking into account information on the upcoming 3 time points and pooling together information on resource availability at the remaining time points at the final time point and reducing the number of temporary distribution centres to be established from 17 to 6.

Conclusion 7: Overall, model IV in combination with redcomb is the best approach

Across all models in combination with all approaches, it can be seen that model IV approached with redcomb leads to the best overall performance. In other words, among all models approached with any methods either exact or heuristic, the process of distributing relief and evacuating injured victims is best performed by using vehicles shared for these activities, taking into account information on the upcoming 3 time points and pooling together information on resource availability at the remaining time points at the last time point and reducing the number of temporary distribution centres to be established from 17 to 6.

Conclusion 8: Information deviation does not affect model performance

Finally, it can be seen that deviation, within certain range, of future information on resource availability considered in the study does not affect the performance of model III and model IV in carrying out the relief distribution and victim evacuation after a sudden-onset, difficult-to-predict natural disaster.

6.2 Research Limitations

It is necessary to mention that the current research is carried out with several limitations. The limitations are highlighted in this section.

The first limitation stems from the maximum deviation of information on future resource availability considered in the current research, which are 0%, 5% and 25%. It is extremely likely that information on future resource availability in practice may deviate more than these values and, thus, the research findings in terms of the effect of information deviation factors (see conclusion 8) may not apply to these larger deviations.

The second limitation concerns the implicit assumption about capacity of sites considered in the current research. Unlimited site capacity is not always the case in context of disaster management and hence it is possible that this may affect the applicability of the findings in the current research.

It is also possible that, following the onset of a disaster, there will not always be an abundant supply of the relief needed by disaster victims. The models presented in this research would, therefore, not be suitable in this situation.

Models II and IV in the current research are built with an assumption that there is a certain authoritative body with capability of giving command to all parties involved in the disaster response. The absence of such ability, therefore, affects the applicability of the models.

6.3 Future Research Directions

Four mathematical models have been built and tested. Performance of the models over various problem sizes has already been presented, many findings have been identified, and overall conclusions have been provided. Considering all of these issues, the following directions of future research can be identified:

Firstly, only one of the six potential combinations of time point reduction heuristics and resource pooling heuristics was explored in the current research, i.e. redcomb heuristic. It might be worthwhile to explore and analyse the relative performance of the other combinations.

Secondly, other near-optimal approaches might be needed to improve the model IV performance. Fixing a particular location-related variable at one and setting the others to zero, for instance, will make the solution space much smaller. A second example would be aggregating the disaster areas into a smaller number, also leading to far smaller solution spaces.

Thirdly, the location-allocation models in the current research are built by using a combination of a *P*-centre model and *P*-median model for the objective functions. In future, location-allocation models for relief distribution and victim evacuation following a sudden-onset, difficult-to-predict natural disaster where coverage to disaster areas is maximised given a particular number of sites (a coverage model) or where maximum value of unmet demands across disaster areas is minimised (a pure *P*-centre model) could be studied. Along with the results of the current research, the results of these last two could subsequently be compared with each other and insights about these approaches obtained.

Fourthly, it is found in the current research that limited deviations of future information on resource availability allowed do not affect the performance of the models. In other words, the current research indicates that deviation of future information on resource availability is not a contributing factor to the four models. It is, nonetheless, a possibility that information on resource availability is not as accurate as that considered in the current research. For this reason, further research could be carried out by taking larger deviation of information into account.

REFERENCES

Ablanedo-Rosas, J. H., Gao, H., Alidaee, B. and Teng, W.-Y. (2009), "Allocation of emergency and recovery centres in Hidalgo, Mexico". *International Journal of Services Sciences*. **2**(2): 206-218.

Abolghasemi, H., Radfar, M. H., Khatami, M., Nia, S. M., Amid, A. and Briggs, S. M. (2006), "International medical response to a natural disaster respose: Lessons learned from the Bam earthquake experience". *Prehospital and Disaster Medicine*. **21**(3): 141-147.

Abounacer, R., Rekik, M. and Renaud, J. (2014), "An exact solution approach for multi-objective location–transportation problem for disaster response". *Computers & Operations Research*. **41**: 83-93.

Adıvar, B. and Mert, A. (2010), "International disaster relief planning with fuzzy credibility". *Fuzzy Optimization and Decision Making*. **9**(4): 413-433.

ADRC (2013). "Multi-language glossary on natural disasters". Retrieved April 13, 2013 from http://image.adrc.or.jp/dbs/translate.asp?lang=en&query=disaster&qtype=1&source=EN&target=EN.

Afshar, A. and Haghani, A. (2012), "Modeling integrated supply chain logistics in real-time large-scale disaster relief operations". *Socio-Economic Planning Sciences*. **46**(4): 327-338.

Akhtar, P., Marr, N. E. and Garnevska, E. V. (2012), "Coordination in humanitarian relief chains: chain coordinators". *Journal of Humanitarian Logistics and Supply Chain Management*. **2**(1): 85-103.

Alcada-Almeida, L., Tralhao, L., Santos, L. and Coutinho-Rodrigues, J. (2009), "A multiobjective approach to locate emergency shelters and identify evacuation route in urban areas". *Geographical Analysis*. **41**: 9-29.

Allua, S. and Thompson, C. B. (2009), "Inferential statistics". *Air Medical Journal*. **28**(4): 168-171.

Altay, N. (2012), "Capability-based resource allocation for effective disaster response". *IMA Journal of Management Mathematics*.

Altay, N. and Green, W. G. (2006), "OR/MS research in disaster operations management". *European Journal of Operational Research*. **175**(1): 475-493.

Ambrosino, D. and Grazia Scutellà, M. (2005), "Distribution network design: New problems and related models". *European Journal of Operational Research*. **165**(3): 610-624.

Ambrosino, D., Sciomachen, A. and Scutellà, M. G. (2009), "A heuristic based on multi-exchange techniques for a regional fleet assignment location-routing problem". *Computers & Operations Research*. **36**(2): 442-460.

An, S., Cui, N., Li, X. and Ouyang, Y. (2013), "Location planning for transit-based evacuation under the risk of service disruptions". *Transportation Research Part B: Methodological*. **54**: 1-16.

Apte, A. (2009), "Humanitarian logistics: a new field of research and action". *Foundations and Trends in Technology, Information and Operations Management*. **3**(1): 1-100.

Apte, A. and Yoho, K. D. (2011), "Strategies for Logistics in Case of a Natural Disaster". Naval Postgraduate School, Graduate School of Business & Public Policy, Monterey, California.

Arora, H., Raghu, T. S. and Vinze, A. (2010), "Resource allocation for demand surge mitigation during disaster response". *Decision Support Systems*. **50**(1): 304-315.

Balcik, B., Beamon, B. and Smilowitz, K. (2008), "Last mile distribution in humanitarian relief". *Journal of Intelligent Transportation Systems*. **12**(2): 51-63.

Balcik, B. and Beamon, B. M. (2008), "Facility location in humanitarian relief". *International Journal of Logistics Research and Applications*. **11**(2): 101-121.

Balcik, B., Beamon, B. M., Krejci, C. C., Muramatsu, K. M. and Ramirez, M. (2010), "Coordination in humanitarian relief chains: Practices, challenges and opportunities". *International Journal of Production Economics*. **126**(1): 22-34.

Baldini, G., Oliveri, F., Braun, M., Seuschek, H. and Hess, E. (2012), "Securing disaster supply chains with cryptography enhanced RFID". *Disaster Prevention and Management*. **21**(1): 51-70.

Baluch, I. (2007), "Delivering relief". *ArabianBusiness.com*. Retrieved April 16, 2013 from http://www.fritzinstitute.org/PDFs/InTheNews/2007/ArabBus_052107.pdf.

Barbarosoğlu, G. and Arda, Y. (2004), "A two-stage stochastic programming framework for transportation planning in disaster response". *Journal of the Operational Research Society*. **55**(1): 43-53.

Barbarosoğlu, G., Ozdamar, L. and Cevik, A. (2002), "An interactive approach for hierarchical analysis of helicopter logistics in disaster relief operations". *European Journal of Operational Research*. **140**: 118-133.

Beamon, B. M. (2004), "Humanitarian relief chains: issues and challenges". *34th International Conference on Computers and Industrial Engineering*. San Francisco: 1-6.

Beamon, B. M. and Balcik, B. (2008), "Performance measurement in humanitarian relief chains". *International Journal of Public Sector Management*. **21**(1): 4-25.

Beamon, B. M. and Kotleba, S. A. (2006), "Inventory management support systems for emergency humanitarian relief operations in South Sudan". *The International Journal of Logistics Management*. **17**(2): 187-212.

Below, R., Grover-Kopec, E. and Dilley, M. (2007), "Documenting drought-related disasters: a global reassessment". *The Journal of Environment Development*. **16**(3): 328-344.

Ben-Tal, A., Chung, B. D., Mandala, S. R. and Yao, T. (2011), "Robust optimization for emergency logistics planning: Risk mitigation in humanitarian relief supply chains". *Transportation Research Part B: Methodological*. **45**(8): 1177-1189.

Berben, L., Sereika, S. M. and Engberg, S. (2012), "Effect size estimation: methods and examples". *Int J Nurs Stud*. **49**(8): 1039-1047.

Berkoune, D., Renaud, J., Rekik, M. and Ruiz, A. (2012), "Transportation in disaster response operations". *Socio-Economic Planning Sciences*. **46**(1): 23-32.

Berman, O., Drezner, Z. and Wesolowsky, G. O. (2007), "The transfer point location problem". *European Journal of Operational Research*. **179**(3): 978-989.

Berman, O., Drezner, Z. and Wesolowsky, G. O. (2008), "The multiple location of transfer points". *Journal of the Operational Research Society*. **59**(6): 805-811.

Bischoff, M. and Dächert, K. (2009), "Allocation search methods for a generalized class of location–allocation problems". *European Journal of Operational Research*. **192**(3): 793-807.

Blum, C. (2005), "Ant colony optimization: Introduction and recent trends". *Physics of Life Reviews*. **2**(4): 353-373.

Blum, C. and Roli, A. (2003), "Metaheuristics in combinatorial optimization: overview and conceptual comparison". *ACM Computing Surveys*. **35**(3): 268-308.

Boin, A., Kelle, P. and Clay Whybark, D. (2010), "Resilient supply chains for extreme situations: outlining a new field of study". *International Journal of Production Economics*. **126**(1): 1-6.

Boloori Arabani, A. and Farahani, R. Z. (2012), "Facility location dynamics: an overview of classifications and applications". *Computers & Industrial Engineering*. **62**(1): 408-420.

Bolsche, D. (2013), "Performance measurement in humanitarian logistics – a process-oriented perspective". *POMS 2013: 24th Annual Conference of the Production and Operations Management Society*. Denver, Colorado.

Bozorgi-Amiri, A., Jabalameli, M. S., Alinaghian, M. and Heydari, M. (2012), "A modified particle swarm optimization for disaster relief logistics under uncertain environment". *The International Journal of Advanced Manufacturing Technology*. **60**(1-4): 357-371.

Bozorgi-Amiri, A., Jabalameli, M. S. and Mirzapour Al-e-Hashem, S. M. J. (2013), "A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty". *OR Spectrum*. **35**(4): 905-933.

BPS (2009), *Penduduk Padang Pariaman Hasil Registrasi Penduduk Akhir Tahun 2008*. Padang Pariaman: Badan Pusat Statistik (BPS) Kabupaten Padang Pariaman.

Buhi, E. R. (2005), "The insignificance of “significance” tests: three recommendations for health education researchers". *American Journal of Health Education*. **36**(2): 109-112.

Bulbul, K., Ulusoy, G. and Sen, A., "Classic Transportation Problems". in Taylor, G. D. (Ed.) (2008), *Logistics Engineering Handbook.* Boca Raton: Taylor & Francis Group.

Campbell, A. M. and Jones, P. C. (2011), "Prepositioning supplies in preparation for disasters". *European Journal of Operational Research*. **209**(2): 156-165.

Caunhye, A. M., Nie, X. and Pokharel, S. (2012), "Optimization models in emergency logistics: a literature review". *Socio-Economic Planning Sciences*. **46**(1): 4-13.

Chaharsooghi, S. K. and Meimand Kermani, A. H. (2008), "An effective ant colony optimization algorithm (ACO) for multi-objective resource allocation problem (MORAP)". *Applied Mathematics and Computation*. **200**(1): 167-177.

Chan, Y., Mahan, J. M., Chrissis, J. W., Drake, D. A. and Wang, D. (2008), "Hierarchical maximal-coverage location–allocation: Case of generalized search-and-rescue". *Computers & Operations Research*. **35**(6): 1886-1904.

Chang, M.-S., Tseng, Y.-L. and Chen, J.-W. (2007), "A scenario planning approach for the flood emergency logistics preparation problem under uncertainty". *Transportation Research Part E: Logistics and Transportation Review*. **43**(6): 737-754.

Charles, A. and Lauras, M. (2011), "An enterprise modelling approach for better optimisation modelling: application to the humanitarian relief chain coordination problem". *OR Spectrum*. **33**(3): 815-841.

Chen, R., Sharman, R., Rao, H. R. and Upadhyaya, S. J. (2008), "Coordination in emergency response management". *Communications of the ACM*. **51**(5): 66-73.

Chern, C. C., Chen, Y. L. and Kung, L. C. (2010), "A heuristic relief transportation planning algorithm for emergency supply chain management". *International Journal of Computer Mathematics*. **87**(7): 1638-1664.

Chi, T.-H., Yang, H. and Hsiao, H.-M. (2011), "A new hierarchical facility location model and genetic algorithm for humanitarian relief". *5th International Conference on New Trends in Information Science and Service Science (NISS)*: 367-374.

Chiu, Y.-C. and Mirchandani, P. B. (2008), "Online behavior-robust feedback information routing strategy for mass evacuation". *IEEE Transactions on Intelligent Transportation Systems*. **9**(2): 264-274.

Chiu, Y.-C. and Zheng, H. (2007), "Real-time mobilization decisions for multi-priority emergency response resources and evacuation groups: Model formulation and solution". *Transportation Research Part E: Logistics and Transportation Review*. **43**(6): 710-736.

Chiu, Y.-C., Zheng, H., Villalobos, J. and Gautam, B. (2007), "Modeling no-notice mass evacuation using a dynamic traffic flow optimization model". *IIE Transactions*. **39**(1): 83-94.

Cho, C.-J. (1998), "AN equity-efficiency trade-off model for the optimum location of medical care facilities". *Socio-Economic Planning Sciences*. **32**(2): 99-122.

Chopra, S. (2003), "Designing the distribution network in a supply chain". *Transportation REsearch part E*. **39**: 123-140.

Chowdhury, J. U., Watkins, D. W., Rahman, M. R. and Karim, M. F. (1998), "Models for Cyclone Shelter Planning in Bangladesh". *Water International*. **23**(3): 155-163.

Cigler, B. A. (2007), "The "big questions" of Katrina and the 2005 great flood of New Orleans". *Public Administration Review*. **67**(s1): 64-76.

Clay Whybark, D. (2007), "Issues in managing disaster relief inventories". *International Journal of Production Economics*. **108**(1-2): 228-235.

Clay Whybark, D., Melnyk, S. A., Day, J. and Davis, E. (2010), "Disaster relief supply chain management: new realities, management challenges, emerging opportunities". *Decision Line*. **May 2010**: 4-7.

Cohen, J. (1992), "A power primer". *Psychological Bulletin*. **112**(1): 155-159.

Coppola, D. P. (2007), *Introduction to International Disaster Management*. Oxford: Butterworth-Heinemann.

Current, J., Daskin, M. and Schilling, D., "Discrete Network Location Models". in Drezner, Z. and Hamacher, H. W. (Ed.) (2001), *Facility Location: Applications and Theory*. Berlin: Springer-Verlag.

Daskin, M. S. (2008), "What you should know about location modeling". *Naval Research Logistics*. **55**(4): 283-294.

Davidson, A. L. (2006), *Key Performance Indicators in Humanitarian Logistics*. **Master of Engineering in Logistics**. Engineering Systems Division, Massachusetts Institute of Technology: 88.

Davis, J. and Lambert, R. (Ed.) (2002), *Engineering in Emergencies: A Practical Guide for Relief Workers*. 2 edition. London: ITDG Publishing.

Day, J. M., Junglas, I. and Silva, L. (2009), "Information flow impediments in disaster relief supply chains". *Journal of the Association for Information Systems*. **10**(8): 637-660.

Day, J. M., Melnyk, S. A., Larson, P. D., Davis, E. W. and Clay Whybark, D. (2012), "Humanitarian and disaster relief supply chains: a matter of life and death". *Journal of Supply Chain Management*. **48**(2): 21-36.

Dekle, J., Lavieri, M. S., Martin, E., Emir-Farinas, H. l. and Francis, R. L. (2005), "A Florida County locates disaster recovery centers". *Interfaces*. **35**(2): 133-139.

Doerner, K. F., Gutjahr, W. J. and Nolz, P. C. (2009), "Multi-criteria location planning for public facilities in tsunami-prone coastal areas". *OR Spectrum*. **31**(3): 651-678.

Döyen, A., Aras, N. and Barbarosoğlu, G. (2011), "A two-echelon stochastic facility location model for humanitarian relief logistics". *Optimization Letters*. **6**(6): 1123-1145.

Drezner, T. (2004), "Location of casualty collection points". *Environment and Planning C: Government and Policy*. **22**: 899-912.

Drezner, T., Drezner, Z. and Salhi, S. (2006), "A multi-objective heuristic approach for the casualty collection points location problem". *Journal of the Operational Research Society*. **57**(6): 727-734.

Dudhia, J., "Fundamental Issues in Numerical Weather Prediction". in Gad-El-Hak, M. (Ed.) (2008), *Large-Scale Disasters: Prediction, Control, and Mitigation*. New York: Cambridge University Press:447-452.

Durlak, J. A. (2009), "How to select, calculate, and interpret effect sizes". *J Pediatr Psychol*. **34**(9): 917-928.

Eben-Chaime, M., Mehrez, A. and Markovich, G. (2002), "Capacitated location-allocation problems on a line". *Computers & Operations Research*. **29**: 459-470.

Edrissi, A., Poorzahedy, H., Nassiri, H. and Nourinejad, M. (2013), "A multi-agent optimization formulation of earthquake disaster prevention and management". *European Journal of Operational Research*. **229**(1): 261-275.

Eikenberry, A. M., Arroyave, V. and Cooper, T. (2007), "Administrative failure and the international NGO response to Hurricane Katrina". *Public Administration Review*. **67**(Supplement s1): 160-170.

EM-DAT (2009), "Classification". *EM-DAT: The OFDA/CRED International Disaster Database – www.emdat.be – Université catholique de Louvain – Brussels – Belgium*. Retrieved April 15, 2013 from http://www.emdat.be/classification.

EM-DAT (2009), "Explanatory Notes". *EM-DAT: The OFDA/CRED International Disaster Database – www.emdat.be – Université catholique de Louvain – Brussels – Belgium*. Retrieved November 6, 2013 from http://www.emdat.be/explanatory-notes.

EM-DAT (2013), "Estimated damage (US$ billion) caused by reported technological disasters 1900-2011". *EM-DAT: The OFDA/CRED International Disaster Database – www.emdat.be – Université catholique de Louvain – Brussels – Belgium*. Retrieved June 13, 2013 from http://www.emdat.be/sites/default/files/Trends/technological/world_1900_2011/tdamyr1.pdf.

EM-DAT (2013), "Natural disaster summary 1900-2011 (linear-interpolated smoothed lines)". *EM-DAT: The OFDA/CRED International Disaster Database – www.emdat.be – Université catholique de Louvain – Brussels – Belgium*. Retrieved June 12, 2013 from http://www.emdat.be/sites/default/files/Trends/natural/world_1900_2011/kefyr1.pdf.

EM-DAT (2013), "Technological disaster summary 1900-2011 (linear-interpolated smoothed lines)". *EM-DAT: The OFDA/CRED International Disaster Database – www.emdat.be – Université catholique de Louvain – Brussels – Belgium*. Retrieved June 13, 2013 from http://www.emdat.be/sites/default/files/Trends/technological/world_1900_2011/tkefyr1.pdf.

EMA (1998), "Australian Emergency Management Glossary". EMA. Retrieved April 14, 2013 from http://www.em.gov.au/Documents/Manual03-AEMGlossary.PDF.

Eshghi, K. and Larson, R. C. (2008), "Disasters: lessons from the past 105 years". *Disaster Prevention and Management*. **17**(1): 62-82.

Falasca, M. and Zobel, C. W. (2011), "A two-stage procurement model for humanitarian relief supply chains". *Journal of Humanitarian Logistics and Supply Chain Management*. **1**(2): 151-169.

Fang, Z., Zong, X., Li, Q., Li, Q. and Xiong, S. (2011), "Hierarchical multi-objective evacuation routing in stadium using ant colony optimization approach". *Journal of Transport Geography*. **19**(3): 443-451.

Fiedrich, F., Gehbauer, F. and Rickers, U. (2000), "Optimized resource allocation for emergency response after earthquake disasters". *Safety Science*. **35**: 41-57.

Fischer, H. W. I. (2008), *Response to Disaster: Fact versus Fiction and Its Perpetuation, The Sociology of Disaster*. 3 edition. Maryland: University Press of America, Inc.

Gad-El-Hak, M. (Ed.) (2008), *Large-Scale Disasters: Prediction, Control, and Mitigation*. New York: Cambridge University Press.

Galindo, G. and Batta, R. (2013), "Prepositioning of supplies in preparation for a hurricane under potential destruction of prepositioned supplies". *Socio-Economic Planning Sciences*. **47**(1): 20-37.

Gatignon, A., Van Wassenhove, L. N. and Charles, A. (2010), "The Yogyakarta earthquake: Humanitarian relief through IFRC's decentralized supply chain". *International Journal of Production Economics*. **126**(1): 102-110.

Ginzburg, E., O'Neill, W. W., Goldschmidt-Clermont, P. J., de Marcena, E., Pust, D. and Green, B. A. (2010), "Rapid medical relief - project Medishare and the Haitian earthquake". *The New England Journal of Medicine*. **362**(e31): 1-3.

Goetschalckx, M., "Distribution System Design". in Taylor, G. D. (Ed.) (2008), *Logistics Engineering Handbook*. Boca Raton: Taylor & Francis Group.

Gong, B., Yang, Z. and Lin, C. (2009), "Dispatching optimization and routing guidance for emergency vehicles in disaster". *IEEE International Conference on Automation and Logistics*. Shenyang, China: 1121-1126.

Gong, Q. and Batta, R. (2007), "Allocation and reallocation of ambulances to casualty clusters in a disaster relief operation". *IIE Transactions*. **39**(1): 27-39.

Guha-Sapir, D., Hargitt, D. and Hoyois, P. (2004), "Thirty Years of Natural Disasters 1974-2003: The Numbers". CRED: 1-188. Retrieved April 13, 2013 from http://www.em-dat.net/documents/Publication/publication_2004_emdat.pdf.

Guha-Sapir, D., Hoyois, P. and Below, R. (2013), "Annual Disaster Statistical Review 2012: The Numbers and Trends". CRED. Retrieved November 6, 2013 from http://cred.be/sites/default/files/ADSR_2012.pdf.

Guha-Sapir, D., Vos, F., Below, R. and Ponserre, S. (2012), "Annual Disaster Statistical Review 2011: The Numbers and Trends". CRED. Retrieved October 22, 2014 from http://www.preventionweb.net/files/27782_adsr2011.pdf.

Haghani, A. and Oh, S.-C. (1996), "Formulation and solution of a multi-commodity, multi-modal network flow model for disaster relief operations". *Transportation Research Part A*. **30**(3): 231-250.

Han, Y., Guan, X. and Shi, L. (2007), "Optimal supply location selection and routing for emergency material delivery". *3rd Annual IEEE Conference on Automation Science and Engineering*. Scottsdale, AZ, USA: 1039-1044.

Han, Y., Guan, X. and Shi, L. (2010), "Optimal supply location selection and routing for emergency material delivery with uncertain demands". *2010 International Conference on Information, Networking and Automation (ICINA)*. Kunming, China: VI-87-VI-92.

Han, Y., Guan, X. and Shi, L. (2011), "Optimization based method for supply location selection and routing in large-scale emergency material delivery". *IEEE Transactions on Automation Science and Engineering*. **8**(4): 683-693.

Harper, P. (2005), "Planning health services with explicit geographical considerations: a stochastic location-allocation approach". *Omega*. **33**(2): 141-152.

Hayat, M. J. (2010), "Understanding statistical significance". *Nursing Research*. **59**(3): 219-223.

Higgins, J. J. (2004), *Introduction to Modern Nonparametric Statistics*. California: Brooks/Cole.

Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N. and Wachtendorf, T. (2012a), "On the unique features of post-disaster humanitarian logistics". *Journal of Operations Management*. **30**(7-8): 494-506.

Holguín-Veras, J., Jaller, M. and Wachtendorf, T. (2012b), "Comparative performance of alternative humanitarian logistic structures after the Port-au-Prince earthquake: ACEs, PIEs, and CANs". *Transportation Research Part A: Policy and Practice*. **46**(10): 1623-1640.

Holguín-Veras, J., Jaller, M. and Wachtendorf, T. (2013), "Improving Postdisaster humanitarian logistics". *TR News*: 4-10. Retrieved November 9, 2013 from http://onlinepubs.trb.org/onlinepubs/trnews/trnews287Postdisaster.pdf.

Hsieh, K.-H. and Tien, F.-C. (2004), "Self-organizing feature maps for solving location–allocation problems with rectilinear distances". *Computers & Operations Research*. **31**(7): 1017-1031.

Hsu, Y.-T. and Peeta, S. (2012), "An aggregate approach to model evacuee behavior for no-notice evacuation operations". *Transportation*. **40**(3): 671-696.

Hsueh, C.-F., Chen, H.-K. and Chou, H.-W., "Dynamic Vehicle Routing for Relief Logistics in Natural Disasters". in Caric, T. and Gold, H. (Ed.) (2008), *Vehicle Routing Problem*. Croatia: In-Teh:71-84.

Hu, F., Xu, W. and Li, X. (2012), "A modified particle swarm optimization algorithm for optimal allocation of earthquake emergency shelters". *International Journal of Geographical Information Science*. **26**(9): 1643-1666.

Huang, R., Kim, S. and Menezes, M. B. C. (2010), "Facility location for large-scale emergencies". *Annals of Operations Research*. **181**(1): 271-286.

Hwang, H.-S. (1999), "A food distribution model for famine relief". *Computers & Industrial Engineering*. **37**: 335-338.

IFRC (2013). "What is a disaster?". Retrieved April 13, 2013 from http://www.ifrc.org/en/what-we-do/disaster-management/about-disasters/what_Is-a-disaster/.

Jargowsky, P. A. and Yang, R. (2005), "Descriptive and inferential statistics". *Encyclopedia of Social Measurement*. **1**: 659-668.

Jia, H., Ordóñez, F. and Dessouky, M. (2007a), "A modeling framework for facility location of medical services for large-scale emergencies". *IIE Transactions*. **39**(1): 41-55.

Jia, H., Ordóñez, F. and Dessouky, M. M. (2007b), "Solution approaches for facility location of medical supplies for large-scale emergencies". *Computers & Industrial Engineering*. **52**(2): 257-276.

Jing, W., Jianming, Z., Jun, H. and Min, Z. (2010), "Multi-level emergency resources location and allocation". *IEEE International Conference on Emergency Management and Management Sciences (ICEMMS)*. Beijing, China: 202-205.

Jotshi, A., Gong, Q. and Batta, R. (2009), "Dispatching and routing of emergency vehicles in disaster mitigation using data fusion". *Socio-Economic Planning Sciences*. **43**(1): 1-24.

Kandel, C., Abidi, H. and Klump, M. (2011), "Humanitarian logistics depot location model". *The 2011 European Simulation and Modelling Conference*. Guimaraes, Portugal: 288-293.

Kapucu, N., Augustin, M.-E. and Garayev, V. (2009), "Interstate partnerships in emergency management: emergency management assistance compact in response to catastrophic disasters". *Public Administration Review*. **69**(2): 297-313.

Keller, E. S. and DeVecchio, D. E. (2012), *Natural Hazards: Earth's Processes as Hazards, Disasters, and Catastrophes*. 3 edition. New Jersey: Pearson Education, Inc.

Kirk, R. E. (2007), "Effect magnitude: A different focus". *Journal of Statistical Planning and Inference*. **137**(5): 1634-1646.

Kongsomsaksakul, S., Yang, C. and Chen, A. (2005), "Shelter location-allocation model for flood evacuation planning". *Journal of the Eastern Asia Society for Transportation Studies*. **6**: 4237-4252.

Kovacs, G. and Spens, K. M. (2011), "Trends and developments in humanitarian logistics - a gap analysis". *International Journal of Physical Distribution & Logistics Management*. **41**(1): 32-45.

Kovács, G. and Spens, K. M. (2007), "Humanitarian logistics in disaster relief operations". *International Journal of Physical Distribution & Logistics Management*. **37**(2): 99-114.

Kovács, G. and Spens, K. M. (2009), "Identifying challenges in humanitarian logistics". *International Journal of Physical Distribution & Logistics Management*. **39**(6): 506-528.

Kovács, G. and Spens, K. M. (2011), "Humanitarian logistics and supply chain management: the start of a new journal". *Journal of Humanitarian Logistics and Supply Chain Management*. **1**(1): 5-14.

Kreiss, Y., Merin, O., Peleg, K., Levy, G., Vinker, S., Sagi, R., Abargel, A., Bartal, C., Lin, G., Bar, A., Bar-On, E., Schwaber, M. J. and Ash, N. (2010), "Early disaster response in Haiti: the Israeli field hospital experience". *Annals of Internal Medicine*. **153**(1): 45-W-26.

Kulshrestha, A., Wu, D., Lou, Y. and Yin, Y. (2011), "Robust shelter locations for evacuation planning with demand uncertainty". *Journal of Transportation Safety & Security*. **3**(4): 272-288.

Kusumastuti, R. D., Wibowo, S. S. and Insanita, R., "Modeling Facility Locations for Relief Logistics in Indonesia". in Zeimpekis, V., Ichoua, S. and Minis, I. (Ed.) (2013), *Humanitarian and Relief Logistics: Research Issues, Case Studies and Future Trends*. 54 edition. New York: Springer:183-206.

Kuwata, Y. and Takada, S. (2004), "Effective emergency transportation for saving human lives". *Natural Hazards*. **33**: 23-46.

Laporte, G. (2007), "What you should know about the vehicle routing problem". *Naval Research Logistics*. **54**(8): 811-819.

Lee, E. K., Chen, C. H., Pietz, F. and Benecke, B. (2009a), "Modeling and optimizing the public-health infrastructure for emergency response". *Interfaces*. **39**(5): 476-490.

Lee, E. K., Maheshwary, S., Mason, J. and Glisson, W. (2006), "Large-scale dispensing for emergency response to bioterrorism and infectious-disease outbreaks". *Interfaces*. **36**(6): 591-607.

Lee, E. K., Smalley, H. N., Zhang, Y., Pietz, F. and Benecke, B. (2009b), "Facility location and multi-modality mass dispensing strategies and emergency response for biodefence and infectious disease outbreaks". *International Journal of Risk Assessment and Management*. **12**(2/3/4): 311-351.

Lei, F. (2007), "Dynamic multi-objective emergency relief logistics: A decision support system framework". *Proceedings of 2007 IEEE International Conference on Grey Systems and Intelligent Services*. Nanjing, China: 779-783.

Lettieri, E., Masella, C. and Radaelli, G. (2009), "Disaster management: findings from a systematic review". *Disaster Prevention and Management*. **18**(2): 117-136.

Li, L. and Jin, M. (2010), "Sheltering planning and management for natural disasters". *THC-IT-2010 Conference & Exhibition*. Texas: 1-10.

Li, S.-l., Ma, Z.-j., Zheng, B. and Dai, Y. (2011), "Multiobjective location-transportation problem in post-earthquake delivery of relief materials". *2011 IEEE 18Th International Conference on Industrial Engineering and Engineering Management (IE&EM)*. Changchun, China: 1468-1472.

Lichterman, J. D. (1999), "Disasters to come". *Futures*. **31**: 593-607.

Lin, Y.-H., Batta, R., Rogerson, P. A., Blatt, A. and Flanigan, M. (2011), "A logistics model for emergency supply of critical items in the aftermath of a disaster". *Socio-Economic Planning Sciences*. **45**(4): 132-145.

Lin, Y.-H., Batta, R., Rogerson, P. A., Blatt, A. and Flanigan, M. (2012), "Location of temporary depots to facilitate relief operations after an earthquake". *Socio-Economic Planning Sciences*. **46**(2): 112-123.

Liu, F.-H. F., Teng, Y.-H. and Lai, C.-H. (2010), "The disaster response performance of hospitals in Taiwan: evaluation and classification". *Quality & Quantity*. **45**(3): 495-511.

Liu, M. and Zhao, L. (2007), "A composite weighted multi-objective optimal approach for emergency logistics distribution". *2007 IEEE International Conference on Industrial Engineering and Engineering Management*. Singapore: 968-972.

Lodree, E. J., Ballard, K. N. and Song, C. H. (2012), "Pre-positioning hurricane supplies in a commercial supply chain". *Socio-Economic Planning Sciences*. **46**(4): 291-305.

Loghmani, A., Jafari, N. and Memarzadeh, M. (2008), "Determining the field hospital setting in earthquake: using RAND/UCLA appropriateness method". *Iranian Red Crescent Medical Journal*. **10**(3): 181-189.

Lu, Q., George, B. and Shekhar, S., "Evacuation Planning: A Capacity Constrained Routing Approach". in Chen, H., Miranda, R., Zeng, D. D., Demchak, C., Schoeder, J. and Madhusudan, T. (Ed.) (2003), *Lecture Notes in Computer Science: Intelligence and Security Informatics*. Berlin Heidelberg: Springer-Verlag. 2665:111-125.

Lu, Q., George, B. and Shekhar, S., "Capacity Constrained Routing Algorithms for Evacuation Planning: A Summary of Results". in Medeiros, C. B., Egenhofer, M. and Bertino, E. (Ed.) (2005), *Lecture Notes in Computer Science: Advances in Spatial and Temporal Databases*. Berlin Heidelberg: Springer-Verlag. 3633:291-307.

Mahecha, R. S. M. and Akhavan-Tabatabaei, R. (2012), "A location model for storage of emergency supplies to respond to technological accidents in Bogota". *2012 Winter Simulation Conference*. Berlin, Germany: 1-12.

Manzini, R. and Gebennini, E. (2008), "Optimization models for the dynamic facility location and allocation problem". *International Journal of Production Research*. **46**(8): 2061-2086.

Marshall, G. and Jonker, L. (2011), "An introduction to inferential statistics: A review and practical guide". *Radiography*. **17**(1): e1-e6.

McCoy, J. H. and Brandeau, M. L. (2011), "Efficient stockpiling and shipping policies for humanitarian relief: UNHCR’s inventory challenge". *OR Spectrum*. **33**(3): 673-698.

McEntire, D. A. (1999), "Issues in disaster relief: progress, perpetual problems and prospective solutions". *Disaster Prevention and Management*. **8**(5): 351-361.

McEntire, D. A. (2002), "Coordinating multi-organisational responses to disaster: lessons from the March 28, 2000, Fort Worth tornado ". *Disaster Prevention and Management*. **11**(5): 369-379.

Memarzadeh, M., Loghmani, A. and Jafari, N. (2004), "The field hospital setting in earthquake". *Journal of Research in Medical Sciences*. **5**: 199-204.

Merin, O., Ash, N., Levy, G., Schwaber, M. J. and Kreiss, Y. (2010), "The Israeli field hospital in Haiti - ethical dilemmas in early disaster response". *the New England Journal of Medicine*. **362**(e38): e38(31)-e38(33).

Mert, A. and Adivar, B. O. (2010), "Fuzzy disaster relief planning with credibility measures". *24th Mini Euro Conference "Continuous Optimization and Information-Based Technologies in the Financial Sector" (MEC EurOPT 2010)*. Izmir, Turkey: 312-317.

Mete, H. O. and Zabinsky, Z. B. (2010), "Stochastic optimization of medical supply location and distribution in disaster management". *International Journal of Production Economics*. **126**(1): 76-84.

Miller, H. E., Engemann, K. J. and Yager, R. R. (2005), "Disaster planning and management". *Communications of the International Information Management Association*. **6**(2): 25-36.

Min, H., Jayaraman, V. and Srivastava, R. (1998), "Combined location-routing problems: a synthesis and future research directions ". *European Journal of Operational Research*. **108**: 1-15.

Mitropoulos, P., Mitropoulos, I., Giannikos, I. and Sissouras, A. (2006), "A biobjective model for the locational planning of hospitals and health centers". *Health Care Management Science*. **9**(2): 171-179.

Moe, T. L., Gehbauer, F., Senitz, S. and Mueller, M. (2007), "Balanced scorecard for natural disaster management projects". *Disaster Prevention and Management*. **16**(5): 785-806.

Moe, T. L. and Pathranarakul, P. (2006), "An integrated approach to natural disaster management: public project management and its critical success factors". *Disaster Prevention and Management*. **15**(3): 396-413.

Murali, P., Ordóñez, F. and Dessouky, M. M. (2012), "Facility location under demand uncertainty: Response to a large-scale bio-terror attack". *Socio-Economic Planning Sciences*. **46**(1): 78-87.

Nagy, G. and Salhi, S. (2007), "Location-routing: Issues, models and methods". *European Journal of Operational Research*. **177**(2): 649-672.

Najafi, M., Eshghi, K. and Dullaert, W. (2013), "A multi-objective robust optimization model for logistics planning in the earthquake response phase". *Transportation Research Part E: Logistics and Transportation Review*. **49**(1): 217-249.

Nolte, I. M., Martin, E. C. and Boenigk, S. (2012), "Cross-sectoral coordination of disaster relief". *Public Management Review*. **14**(6): 707-730.

Norio, O., Ye, T., Kajitani, Y., Shi, P. and Tatano, H. (2012), "The 2011 Eastern Japan great earthquake disaster: overview and comments". *International Journal of Disaster Risk Science*. **2**(1): 34-42.

Oh, S. C. and Haghani, A. (1997), " Testing and evaluation of a multi-commodity multi-modal network flow model for disaster relief management". *Journal of Advanced Transportation*. **31**(3): 249-282.

Oloruntoba, R. (2005), "A wave of destruction and the waves of relief: issues, challenges and strategies". *Disaster Prevention and Management*. **14**(4): 506-521.

Ortuño, M. T., Tirado, G. and Vitoriano, B. (2010), "A lexicographical goal programming based decision support system for logistics of Humanitarian Aid". *Top*. **19**(2): 464-479.

Owen, S. H. and Daskin, M. S. (1998), "Strategic facility location: a review". *European Journal of Operational Research*. **111**: 423-447.

Ozdamar, L. (2011), "Planning helicopter logistics in disaster relief". *OR Spectrum*. **33**(3): 655-672.

Özdamar, L. and Demir, O. (2012), "A hierarchical clustering and routing procedure for large scale disaster relief logistics planning". *Transportation Research Part E: Logistics and Transportation Review*. **48**(3): 591-602.

Ozdamar, L., Ekinci, E. and Kucukyazici, B. (2004), "Emergency logistics planning in natural disasters". *Annals of Operations Research*. **129**: 217-245.

Ozdamar, L. and Yi, W. (2008), "Greedy neighborhood search for disaster relief and evacuation logistics". *IEEE Intelligent Systems*. **23**(1): 14-23.

Park, S., van de Lindt, J. W., Gupta, R. and Cox, D. (2012), "Method to determine the locations of tsunami vertical evacuation shelters". *Natural Hazards*. **63**(2): 891-908.

Paul, J. A. and Hariharan, G. (2012), "Location-allocation planning of stockpiles for effective disaster mitigation". *Annals of Operations Research*. **196**(1): 469-490.

Paul, J. M. and Batta, R. (2008), "Models for hospital location and capacity allocation for an area prone to natural disasters". *International Journal of Operational Research*. **3**(5): 473-496.

Pedraza Martinez, A. J., Stapleton, O. and Van Wassenhove, L. N. (2011), "Field vehicle fleet management in humanitarian operations: A case-based approach". *Journal of Operations Management*. **29**(5): 404-421.

Perry, M. (2007), "Natural disaster management planning: a study of logistics managers responding to the tsunami". *International Journal of Physical Distribution & Logistics Management*. **37**(5): 409-433.

Pettit, S. and Beresford, A. (2005), "Emergency relief logistics: an evaluation of military, non-military and composite response models". *International Journal of Logistics*. **8**(4): 313-331.

Pettit, S. and Beresford, A. (2009), "Critical success factors in the context of humanitarian aid supply chains". *International Journal of Physical Distribution & Logistics Management*. **39**(6): 450-468.

Ponterotto, J. G. (2006), "Brief note on the origins, evolution, and meaning of the qualitative research concept "thick description"". *The Qualitative Report*. **11**(3): 538-549.

Portilla, D., Shaffer, R. N., Okusa, M. D., Mehrotra, R., Molitoris, B. A., Bunchman, T. E. and Ibrahim, T. (2010), "Lessons from Haiti on disaster relief". *Clinical Journal of the American Society of Nephrology*. **5**(11): 2122-2129.

Prizzia, R., "The Role of Coordination in Disaster Management". in Pinkowski, J. (Ed.) (2008), *Disaster Management Handbook*. Boca Raton: CRC Press.

Pujawan, I. N., Kurniati, N. and Wessiani, N. A. (2009), "Supply chain management for Disaster Relief Operations: principles and case studies". *International Journal of Logistics Systems and Management*. **5**(6): 679-692.

Rachaniotis, N. P., Dasaklis, T., Pappis, C. P. and Van Wassenhove, L. N., "Multiple Location and Routing Models in Humanitarian Logistics". in Zeimpekis, V., Ichoua, S. and Minis, I. (Ed.) (2013), *Humanitarian and Relief Logistics: Research Issues, Case Studies and Future Trends*. New York: Springer Science. 54:43-57.

Rath, S. and Gutjahr, W. J. (2014), "A math-heuristic for the warehouse location–routing problem in disaster relief". *Computers & Operations Research*. **42**: 25-39.

Ratick, S., Meacham, B. and Aoyama, Y. (2008), "Locating backup facilities to enhance supply chain disaster resilience". *Growth and Change*. **39**(4): 642-666.

Rawls, C. G. and Turnquist, M. A. (2010), "Pre-positioning of emergency supplies for disaster response". *Transportation Research Part B: Methodological*. **44**(4): 521-534.

Rawls, C. G. and Turnquist, M. A. (2011), "Pre-positioning planning for emergency response with service quality constraints". *OR Spectrum*. **33**(3): 481-498.

Rawls, C. G. and Turnquist, M. A. (2012), "Pre-positioning and dynamic delivery planning for short-term response following a natural disaster". *Socio-Economic Planning Sciences*. **46**(1): 46-54.

Rekik, M., Ruiz, A., Renaud, J., Berkoune, D. and Paquet, S., "A Decision Support System for Humanitarian Network Design and Distribution Operations". in Zeimpekis, V., Ichoua, S. and Minis, I. (Ed.) (2013), *Humanitarian and Relief Logistics: Research Issues, Case Studies and Future Trends*. New York: Springer Science. 54:1-20.

ReVelle, C. S. and Eiselt, H. A. (2005), "Location analysis: A synthesis and survey". *European Journal of Operational Research*. **165**(1): 1-19.

ReVelle, C. S., Eiselt, H. A. and Daskin, M. S. (2008), "A bibliography for some fundamental problem categories in discrete location science". *European Journal of Operational Research*. **184**(3): 817-848.

Rosen, J., Grigg, E., Lanier, J., McGrath, S., Lillibridge, S., Sargent, D. and Koop, C. E. (2002), "The future of command and control for disaster response". *IEEE Engineering in Medicine and Biology Magazine*. **21**(5): 56-68.

Rottkemper, B., Fischer, K. and Blecken, A. (2012), "A transshipment model for distribution and inventory relocation under uncertainty in humanitarian operations". *Socio-Economic Planning Sciences*. **46**(1): 98-109.

Rottkemper, B., Fischer, K., Blecken, A. and Danne, C. (2011), "Inventory relocation for overlapping disaster settings in humanitarian operations". *OR Spectrum*. **33**(3): 721-749.

Russell, T. E. (2005), *The Humanitarian Relief Supply Chain: Analysis of the 2004 South East Asia Earthquake and Tsunami*. **Master of Engineering in Logistics**, Massachusetts Institute of Technology: 117.

Saadatseresht, M., Mansourian, A. and Taleai, M. (2009), "Evacuation planning using multiobjective evolutionary optimization approach". *European Journal of Operational Research*. **198**(1): 305-314.

Salmeron, J. and Apte, A. (2010), "Stochastic optimization for natural disaster asset prepositioning". *Production and Operations Management*. **19**(5): 561-574.

Santarelli, G., Abidi, H., Regattieri, A. and Klumpp, M. (2013), "A performance measurement system for the evaluation of humanitarian supply chains". *POMS 2013: 24th Annual Conference of the Production and Operations Management Society*. Denver, Colorado.

Sayyady, F. and Eksioglu, S. D. (2010), "Optimizing the use of public transit system during no-notice evacuation of urban areas". *Computers & Industrial Engineering*. **59**(4): 488-495.

Schmid, V. and Doerner, K. F. (2010), "Ambulance location and relocation problems with time-dependent travel times". *European Journal of Operational Research*. **207**(3): 1293-1303.

Schulz, S. F. and Blecken, A. (2010), "Horizontal cooperation in disaster relief logistics: benefits and impediments". *International Journal of Physical Distribution & Logistics Management*. **40**(8): 636-656.

Schulz, S. F. and Heigh, I. (2009), "Logistics performance management in action within a humanitarian organization". *Management Research News*. **32**(11): 1038-1049.

Segall, R. S. (2000), "Some quantitative methods for determining capacities and locations of military emergency medical facilities". *Applied Mathematical Modelling*. **24**: 365-389.

Sherali, H. D., Carter, T. B. and Hobeika, A. G. (1991), "A location-allocation model and algorithm for evacuation planning under hurricane/ flood conditions". *Transportation Research Part B*. **25B**(6): 439-452.

Sheu, J.-B. (2007a), "Challenges of emergency logistics management". *Transportation Research Part E: Logistics and Transportation Review*. **43**(6): 655-659.

Sheu, J.-B. (2007b), "An emergency logistics distribution approach for quick response to urgent relief demand in disasters". *Transportation Research Part E: Logistics and Transportation Review*. **43**(6): 687-709.

Sheu, J.-B. (2010), "Dynamic relief-demand management for emergency logistics operations under large-scale disasters". *Transportation Research Part E: Logistics and Transportation Review*. **46**(1): 1-17.

Smith, H. K., Laporte, G. and Harper, P. R. (2009), "Locational analysis: highlights of growth to maturity". *Journal of the Operational Research Society*. **60**: S140-S148.

Snyder, L. V., Daskin, M. S. and Teo, C.-P. (2007), "The stochastic location model with risk pooling". *European Journal of Operational Research*. **179**(3): 1221-1238.

Stepanov, A. and Smith, J. M. (2009), "Multi-objective evacuation routing in transportation networks". *European Journal of Operational Research*. **198**(2): 435-446.

Tatham, P. and Kovács, G. (2010), "The application of “swift trust” to humanitarian logistics". *International Journal of Production Economics*. **126**(1): 35-45.

Telford, J. and Cosgrave, J. (2006), "Joint evaluation of the international response to the Indian Ocean tsunami: Synthesis Report". Tsunami Evaluation Coalition (TEC): 191. Retrieved October 28, 2013 from http://www.sida.se/Publications/Import/pdf/sv/Joint-Evaluation-of-the-International-Response-to-the-Indian-Ocean-Tsunami_3141.pdf.

Thévenaz, C. and Resodihardjo, S. L. (2010), "All the best laid plans…conditions impeding proper emergency response". *International Journal of Production Economics*. **126**(1): 7-21.

Thomas, A. (2005), "Improving aid effectiveness: two studies suggest solutions". *UN Chronicle*. **4**: 61-63.

Thomas, A. (2006), "The changing tide of aid provision". *Georgetown Journal of International Affairs*. **Summer/Fall 2006**: 83-89.

Thomas, A. and Kopczak, L. R. (2005a), "From logistics to supply chain management: the path forward in the humanitarian sector". Fritz Institute.

Retrieved April 15, 2013 from http://www.fritzinstitute.org/pdfs/whitepaper/fromlogisticsto.pdf.

Thomas, A. S. and Kopczak, L. R. (2005b), "From logistics to supply chain management: the path forward in the humanitarian sector". Fritz Institute. Retrieved April 15, 2013 from http://www.fritzinstitute.org/pdfs/whitepaper/fromlogisticsto.pdf

Thompson, B. (2006), *Foundations of Behavioral Statistics: An Insight-Based Approach*. New York: The Guilford Press.

Tierney, K. J., Lindell, M. K. and Perry, R. W. (2003), *Facing the Unexpected: Disaster Preparedness and Response in the United States*. Washington, D.C.: Joseph Henry Press.

Tomasini, R. and van Wassenhove, L. (2009), *Humanitarian Logistics*. London: Palgrave McMillan.

Torabi, S. A. (2013), "A framework for performance measurement of humanitarian relief chains: a combined fuzzy DEMATEL-ANP approach". *POMS 2013: 24th Annual Conference of the Production and Operations Management Society*. Denver, Colorado.

Tovia, F. (2007), "An emergency logistics response system for natural disasters". *International Journal of Logistics Research and Applications*. **10**(3): 173-186.

Tzeng, G.-H., Cheng, H.-J. and Huang, T. D. (2007), "Multi-objective optimal planning for designing relief delivery systems". *Transportation Research Part E: Logistics and Transportation Review*. **43**(6): 673-686.

Ukkusuri, S. V. and Yushimito, W. F. (2008), "Location routing approach for the humanitarian prepositioning problem". *Transportation Research Record: Journal of the Transportation Research Board*. **2089**: 18-25.

UNISDR (2004), *Living with Risk: A Global Review of Disaster Reduction Initiatives*. Geneva: United Nations.

UNISDR (2009), "2009 UNISDR Terminology on Disaster Risk Reduction". United Nations: 01-30. Retrieved April 13, 2013 from http://www.unisdr.org/files/7817_UNISDRTerminologyEnglish.pdf.

UNISDR (2013), "2012 Disasters in Numbers". *UNISDR*. Retrieved May 2, 2013 from http://www.preventionweb.net/files/31685_factsheet2012.pdf.

UNISDR (2013), "Disaster Impacts 2000-2012". *UNISDR*. Retrieved April 15, 2013 from http://www.preventionweb.net/files/31737_20130312disaster20002012copy.pdf.

ÜSter, H., Keskin, B. B. and ÇEtinkaya, S. (2008), "Integrated warehouse location and inventory decisions in a three-tier distribution system". *IIE Transactions*. **40**(8): 718-732.

van Rossum, J. and Krukkert, R. (2010), "Disaster management in Indonesia: logistical coordination and cooperation to create effective relief operations". *Jurnal Teknik Industri*. **12**(1): 25-32.

Van Wassenhove, L. N. (2003), "New interesting POM cases from Europe: a message from POMS regional VP - Luk Van Wassenhove". *POMS Cronicle*. **2**: 19. Retrieved April 16, 2013 from http://www.poms.org/chronicle/vol10no2.pdf.

Van Wassenhove, L. N. (2006), "Humanitarian aid logistics: supply chain management in high gear†". *Journal of the Operational Research Society*. **57**(5): 475-489.

Vitoriano, B., Ortuño, M. T., Tirado, G. and Montero, J. (2010), "A multi-criteria optimization model for humanitarian aid distribution". *Journal of Global Optimization*. **51**(2): 189-208.

Vitoriano, B., Ortuño, T. and Tirado, G. (2009), "HADS, a goal programming-based humanitarian aid distribution system". *Journal of Multi-Criteria Decision Analysis*. **16**(1-2): 55-64.

Wen, M. and Iwamura, K. (2008), "Fuzzy facility location-allocation problem under the Hurwicz criterion". *European Journal of Operational Research*. **184**(2): 627-635.

Wenxue, C. and Zihui, Z. (2010), "Path selection evaluation for emergency transport vehicles". *2010 International Conference on Logistics Systems and Intelligent Management*. Harbin, China: 1050-1054.

Widener, M. J. and Horner, M. W. (2011), "A hierarchical approach to modeling hurricane disaster relief goods distribution". *Journal of Transport Geography*. **19**(4): 821-828.

Wu, Y.-C. J. and Huang, I. C. (2007), "Operations research practice on logistics management in Taiwan: an academic view". *European Journal of Operational Research*. **182**(1): 428-435.

Xiang-lin, L. and Yun-xian, H. (2009a), "Ant colony optimization for facility location for large-scale emergencies". *International Conference on Management and Service Science*. Wuhan/ Beijing, China: 1-4.

Xiang-lin, L. and Yun-xian, H. (2009b), "A grey degree model for facility location in large-scale emergencies". *IEEE International Conference on Grey Systems*. Nanjing, China: 1152-1157.

Xiang-lin, L., Yun-xian, H. and Qiang, S. (2010), "A fuzzy queuing facility location model with ant colony optimization algorithm for large-scale emergencies". *7th International Conference on Service Systems and Service Management (ICSSSM)*. Tokyo: 1-6.

Xue, H., Wei, S. and Yang, L. (2012), "Research on the locating model and algorithm of multiple relief centers". *Journal of Convergence Information Technology*. **7**(15): 99-106.

Yan, S. and Shih, Y.-L. (2009), "Optimal scheduling of emergency roadway repair and subsequent relief distribution". *Computers & Operations Research*. **36**(6): 2049-2065.

Yao, Z., Lee, L. H., Jaruphongsa, W., Tan, V. and Hui, C. F. (2010), "Multi-source facility location–allocation and inventory problem". *European Journal of Operational Research*. **207**(2): 750-762.

Yi, W. and Kumar, A. (2007), "Ant colony optimization for disaster relief operations". *Transportation Research Part E: Logistics and Transportation Review*. **43**(6): 660-672.

Yi, W. and Özdamar, L. (2007), "A dynamic logistics coordination model for evacuation and support in disaster response activities". *European Journal of Operational Research*. **179**(3): 1177-1193.

Yin, P.-Y. and Wang, J.-Y. (2006a), "Ant colony optimization for the nonlinear resource allocation problem". *Applied Mathematics and Computation*. **174**(2): 1438-1453.

Yin, P.-Y. and Wang, J.-Y. (2006b), "A particle swarm optimization approach to the nonlinear resource allocation problem". *Applied Mathematics and Computation*. **183**(1): 232-242.

Yuan, Y. and Wang, D. (2009), "Path selection model and algorithm for emergency logistics management". *Computers & Industrial Engineering*. **56**(3): 1081-1094.

Yushimito, W. F., Jaller, M. and Ukkusuri, S. (2010), "A Voronoi-based heuristic algorithm for locating distribution centers in disasters". *Networks and Spatial Economics*. **12**(1): 21-39.

Zeimpekis, V., Ichoua, S. and Minis, I. (Ed.) (2013), *Humanitarian and Relief Logistics: Research Issues, Case Studies and Future Trends*. New York: Springer Science.

Zhan, S.-l. and Liu, N. (2011), "A multi-objective stochastic programming model for emergency logistics based on goal programming". *2011 Fourth International Joint Conference on Computational Sciences and Optimization*. Yunnan, China: 640-644.

Zhang, J., Dong, M. and Frank Chen, F. (2013), "A bottleneck Steiner tree based multi-objective location model and intelligent optimization of emergency logistics systems". *Robotics and Computer-Integrated Manufacturing*. **29**(3): 48-55.

Zhou, J. and Liu, B. (2003), "New stochastic models for capacitated location-allocation problem". *Computers & Industrial Engineering*. **45**(1): 111-125.

Zhou, J. and Liu, B. (2007), "Modeling capacitated location–allocation problem with fuzzy demands". *Computers & Industrial Engineering*. **53**(3): 454-468.

Zhu, J., Huang, J., Liu, D. and Han, J. (2008), "Resources allocation problem for local reserve depots in disaster management based on scenario analysis". *7th International Symposium on Operations Research and Its Applications (ISORA'08)*. Lijiang, China: 395–407.

Zhu, J., Liu, D., Huang, J. and Han, J. (2010), "Determining storage locations and capacities for emergency response". *The Ninth International Symposium on Operations Research and Its Applications (ISORA'10)*. Chengdu-Jiuzhaigou, China: 262-269.

Zlochin, M., Birattari, M., Meuleau, N. and Dorigo, M. (2004), "Model-based search for combinatorial optimization: a critical survey". *Annals of Operations Research*. **131**: 373-395.

Appendix A Computational Results of Various Problem Sizes with Regard to Models

Table A.1 Maximum objective values of NT11R3Na9_0%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	27,496,072.739924	14,797,590.862604	21,148,781.340096	11,669,679.064412
2	12,850,892.155994	7,925,306.849661	11,790,607.737319	7,865,795.879801
3	9,308,047.914599	1,807,843.513970	3,491,390.822878	1,697,430.996012
4	10,123,668.949215	3,561,886.964881	6,327,357.705672	2,730,133.730527
5	7,299,454.766612	5,430,558.609666	8,433,567.384927	6,391,967.561995
6	10,902,896.386778	4,650,579.334647	9,585,765.910113	4,802,707.250711
7	8,135,652.649626	3,242,428.685901	5,715,355.433492	2,364,376.299961
8	29,218,685.817938	6,278,197.803867	25,428,504.094245	8,031,270.587931
9	29,650,660.924359	6,814,770.588185	16,175,249.043412	5,197,598.391291
10	35,264,939.281235	3,579,559.854543	14,972,538.885377	3,282,783.035733
Average	18,025,097.158628	5,808,872.306793	12,306,911.835753	5,403,374.279837
StdDev	10,934,755.338177	3,660,705.145855	7,086,885.669887	3,131,010.533937

Table A.2 Maximum objective values of NT11R3Na9_5%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	27,496,072.739924	14,797,590.862604	22,991,386.587297	11,380,897.704051
2	12,850,892.155994	7,925,306.849661	11,198,873.458663	5,615,891.037599
3	9,308,047.914599	1,807,843.513970	3,514,233.435463	1,806,746.754842
4	10,123,668.949215	3,561,886.964881	6,661,750.339148	2,726,084.834423
5	7,299,454.766612	5,430,558.609666	7,121,040.925222	4,797,457.092805
6	10,902,896.386778	4,650,579.334647	9,675,266.985987	5,256,191.327832
7	8,135,652.649626	3,242,428.685901	6,475,869.577779	3,024,789.632159
8	29,218,685.817938	6,278,197.803867	26,311,558.617415	8,228,759.410218
9	29,650,660.924359	6,814,770.588185	15,527,220.081441	4,496,071.535722
10	35,264,939.281235	3,579,559.854543	16,856,045.899602	4,528,453.618110
Average	18,025,097.158628	5,808,872.306793	12,633,324.590802	5,186,134.294776
StdDev	10,934,755.338177	3,660,705.145855	7,590,303.328781	2,809,222.407836

Table A.3 Maximum objective values of NT11R3Na9_25%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	27,496,072.739924	14,797,590.862604	22,562,021.798995	9,287,419.827389
2	12,850,892.155994	7,925,306.849661	12,370,567.184702	5,037,224.225881
3	9,308,047.914599	1,807,843.513970	3,454,039.453198	1,531,216.205797
4	10,123,668.949215	3,561,886.964881	6,392,158.104694	2,382,666.638338
5	7,299,454.766612	5,430,558.609666	8,241,825.733995	5,725,194.729944
6	10,902,896.386778	4,650,579.334647	9,689,406.566231	4,316,024.347895
7	8,135,652.649626	3,242,428.685901	4,733,998.313075	2,711,623.191098
8	29,218,685.817938	6,278,197.803867	23,867,922.982875	8,305,270.645346
9	29,650,660.924359	6,814,770.588185	13,406,297.969237	6,881,823.939478
10	35,264,939.281235	3,579,559.854543	16,156,512.636327	3,139,003.641372
Average	18,025,097.158628	5,808,872.306793	12,087,475.074333	4,931,746.739254
StdDev	10,934,755.338177	3,660,705.145855	7,058,940.757576	2,611,501.177777

Table A.4 Maximum objective values of NT16R3Na9_0%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	40,700,090.824330	6,463,730.436336	25,465,423.504612	4,784,372.666265
2	21,649,322.410477	7,430,392.328165	20,705,820.710866	5,952,910.792351
3	15,126,710.623879	2,676,209.909217	5,499,908.987310	1,889,494.790229
4	11,305,275.565013	3,679,561.366851	6,479,564.105414	4,236,365.301081
5	11,113,169.414756	7,269,280.261371	8,529,269.686760	6,104,356.949446
6	18,763,045.948810	3,438,552.043719	14,368,031.030648	4,200,372.088441
7	11,797,515.061305	2,407,531.080262	8,860,695.397658	1,302,947.327156
8	55,154,998.286859	5,642,540.617233	38,147,411.176100	4,849,240.473492
9	60,792,581.539081	5,869,604.961510	21,764,587.486102	4,865,901.584367
10	64,306,464.706932	5,414,299.732272	13,884,059.952069	4,712,064.969867
Average	31,070,917.438144	5,029,170.273694	16,370,477.203754	4,289,802.694270
StdDev	21,897,912.325695	1,850,937.492401	10,268,167.451492	1,557,060.533469

Table A.5 Maximum objective values of NT16R3Na9_5%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	40,700,090.824330	6,463,730.436336	21,132,124.015056	8,465,770.509367
2	21,649,322.410477	7,430,392.328165	20,629,674.607517	4,452,191.283850
3	15,126,710.623879	2,676,209.909217	6,587,442.316373	1,254,619.821103
4	11,305,275.565013	3,679,561.366851	8,006,048.692975	3,116,125.836945
5	11,113,169.414756	7,269,280.261371	9,149,446.517002	7,863,363.331722
6	18,763,045.948810	3,438,552.043719	15,405,014.020861	4,365,541.475853
7	11,797,515.061305	2,407,531.080262	8,849,276.591830	1,973,135.030791
8	55,154,998.286859	5,642,540.617233	36,884,260.782816	4,790,121.358347
9	60,792,581.539081	5,869,604.961510	21,915,407.414311	6,132,095.031639
10	64,306,464.706932	5,414,299.732272	13,515,758.884984	3,947,644.874863
Average	31,070,917.438144	5,029,170.273694	16,207,445.384373	4,636,060.855448
StdDev	21,897,912.325695	1,850,937.492401	9,283,046.264188	2,327,622.425348

Table A.6 Maximum objective values of NT16R3Na9_25%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	40,700,090.824330	6,463,730.436336	25,239,212.976405	12,250,539.154052
2	21,649,322.410477	7,430,392.328165	21,060,121.046579	4,663,712.950460
3	15,126,710.623879	2,676,209.909217	5,224,007.979792	1,570,035.946555
4	11,305,275.565013	3,679,561.366851	6,126,345.326964	3,755,086.824460
5	11,113,169.414756	7,269,280.261371	6,091,125.089704	7,355,135.133507
6	18,763,045.948810	3,438,552.043719	15,017,957.538736	4,503,993.359512
7	11,797,515.061305	2,407,531.080262	8,303,390.208838	2,473,962.195141
8	55,154,998.286859	5,642,540.617233	38,381,952.883687	5,727,640.678413
9	60,792,581.539081	5,869,604.961510	22,753,162.681307	5,446,940.077235
10	64,306,464.706932	5,414,299.732272	15,446,193.655336	6,560,522.914957
Average	31,070,917.438144	5,029,170.273694	16,364,346.938735	5,430,756.923429
StdDev	21,897,912.325695	1,850,937.492401	10,690,095.048688	2,971,725.147855

Table A.7 Maximum objective values of NT11R17Na47_0%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	11,770,696.783953	2,040,220.824428	2,365,612.625714	2,695,292.333730
2	4,176,392.930556	1,073,476.155677	1,214,832.020031	1,249,086.986735
3	3,407,351.387036	1,602,558.137711	1,823,488.343422	1,338,713.913235
4	3,185,464.524892	1,556,591.235850	1,842,592.642589	794,366.642666
5	3,335,728.111255	1,277,832.770887	2,317,349.131628	1,004,738.706823
6	3,474,015.140546	881,815.234512	2,174,769.823813	1,236,645.358194
7	3,926,879.634802	1,290,944.221342	1,539,182.841400	1,221,631.809938
8	16,042,396.850427	2,618,698.408712	2,063,471.661733	1,800,359.925294
9	7,798,546.680230	2,920,322.214918	1,039,642.841582	1,771,716.937979
10	8,154,479.741146	2,045,702.298207	2,004,274.642664	2,554,760.412222
Average	6,527,195.178484	1,730,816.150224	1,838,521.657458	1,566,731.302682
StdDev	4,409,505.303549	666,377.290458	449,108.060652	635,939.903162

Table A.8 Maximum objective values of NT11R17Na47_5%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	11,770,696.783953	2,040,220.824428	2,453,152.174958	3,181,723.079483
2	4,176,392.930556	1,073,476.155677	1,069,559.846660	1,498,241.562424
3	3,407,351.387036	1,602,558.137711	1,768,972.183566	1,231,496.757748
4	3,185,464.524892	1,556,591.235850	1,869,963.912549	1,275,652.654880
5	3,335,728.111255	1,277,832.770887	1,665,362.359842	1,607,842.834539
6	3,474,015.140546	881,815.234512	1,833,958.960282	1,544,125.626526
7	3,926,879.634802	1,290,944.221342	1,713,497.323002	1,508,600.644305
8	16,042,396.850427	2,618,698.408712	1,519,462.821665	2,055,097.612756
9	7,798,546.680230	2,920,322.214918	1,118,388.969060	1,851,015.292716
10	8,154,479.741146	2,045,702.298207	2,121,536.228254	3,638,805.047886
Average	6,527,195.178484	1,730,816.150224	1,713,385.477984	1,939,260.111326
StdDev	4,409,505.303549	666,377.290458	416,924.050070	819,255.090089

Table A.9 Maximum objective values of NT11R17Na47_25%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	11,770,696.783953	2,040,220.824428	2,500,468.851719	3,447,826.759728
2	4,176,392.930556	1,073,476.155677	1,601,946.599437	715,181.416597
3	3,407,351.387036	1,602,558.137711	2,072,117.308556	1,138,194.608328
4	3,185,464.524892	1,556,591.235850	1,991,723.885238	1,707,614.574457
5	3,335,728.111255	1,277,832.770887	1,465,863.941672	2,400,471.082415
6	3,474,015.140546	881,815.234512	1,955,079.632090	1,875,074.450099
7	3,926,879.634802	1,290,944.221342	1,188,689.248871	577,684.303681
8	16,042,396.850427	2,618,698.408712	1,764,008.447856	2,108,647.773121
9	7,798,546.680230	2,920,322.214918	1,218,586.401854	1,563,612.607889
10	8,154,479.741146	2,045,702.298207	2,026,141.608899	3,349,722.798291
Average	6,527,195.178484	1,730,816.150224	1,778,462.592619	1,888,403.037461
StdDev	4,409,505.303549	666,377.290458	413,107.957876	981,697.815908

Table A.10 Maximum objective values of NT16R17Na47_0%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	15,940,298.888439	4,109,663.298415	2,968,072.739592	3,362,237.493048
2	4,968,099.604964	1,990,637.994332	862,163.548929	4,294,379.565859
3	3,205,787.471009	2,036,532.106949	1,898,448.429695	1,874,546.436309
4	2,935,706.189094	1,492,224.961241	1,778,917.348305	2,128,097.362321
5	4,623,659.767271	2,518,035.666899	1,942,710.103086	2,990,622.103603
6	5,935,894.485852	3,788,185.011062	2,390,011.487930	3,039,828.967085
7	5,212,942.865448	2,863,088.233767	1,568,108.981696	2,433,033.651523
8	31,866,915.512386	2,733,763.586319	2,604,545.915556	3,162,028.931228
9	12,575,514.930374	2,448,016.751797	913,690.729785	1,800,858.280938
10	15,082,770.251549	2,140,497.812083	1,683,872.211070	2,266,259.296524
Average	10,234,758.996639	2,612,064.542286	1,861,054.149564	2,735,189.208844
StdDev	9,037,510.437003	811,956.652944	673,743.167643	778,741.265913

Table A.11 Maximum objective values of NT16R17Na47_5%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	15,940,298.888439	4,109,663.298415	2,944,238.918354	4,338,602.209476
2	4,968,099.604964	1,990,637.994332	1,089,987.594516	1,971,116.722639
3	3,205,787.471009	2,036,532.106949	1,789,263.331464	1,566,146.813125
4	2,935,706.189094	1,492,224.961241	2,205,880.777343	2,656,291.950534
5	4,623,659.767271	2,518,035.666899	1,194,046.872159	2,482,018.029852
6	5,935,894.485852	3,788,185.011062	2,499,306.782209	1,939,591.555800
7	5,212,942.865448	2,863,088.233767	1,392,015.979507	2,880,135.774143
8	31,866,915.512386	2,733,763.586319	2,212,565.966628	2,799,027.633121
9	12,575,514.930374	2,448,016.751797	1,039,777.396222	1,501,827.714255
10	15,082,770.251549	2,140,497.812083	1,793,905.359049	4,047,578.144981
Average	10,234,758.996639	2,612,064.542286	1,816,098.897745	2,618,233.654793
StdDev	9,037,510.437003	811,956.652944	645,196.732540	963,589.372983

Table A.12 Maximum objective values of NT16R17Na47_25%

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	15,940,298.888439	4,109,663.298415	2,629,433.804096	3,304,310.151033
2	4,968,099.604964	1,990,637.994332	920,044.897901	2,148,796.764682
3	3,205,787.471009	2,036,532.106949	2,163,744.710639	2,442,061.355635
4	2,935,706.189094	1,492,224.961241	1,356,399.579757	1,641,725.611882
5	4,623,659.767271	2,518,035.666899	1,689,840.768122	2,250,003.416972
6	5,935,894.485852	3,788,185.011062	2,185,581.053416	1,393,255.882212
7	5,212,942.865448	2,863,088.233767	2,124,438.087910	1,776,576.381494
8	31,866,915.512386	2,733,763.586319	1,933,338.841560	3,443,854.664635
9	12,575,514.930374	2,448,016.751797	926,488.607686	2,070,410.999865
10	15,082,770.251549	2,140,497.812083	1,977,397.864914	3,029,133.361595
Average	10,234,758.996639	2,612,064.542286	1,790,670.821600	2,350,012.859001
StdDev	9,037,510.437003	811,956.652944	564,588.533398	703,278.191808

Appendix B A Note on Statistical Tests in the Thesis and the Effect Size Calculation

Note on Statistical Tests

Because data for testing the models for a certain problem (i.e. the maximum objective values resulting from the application of the models to the problem) are samples from a population (i.e. all possible maximum objective values resulting from the application of the models to the problem), insights can, therefore, be obtained by applying appropriate methods of inferential statistics (see, for instance, Allua and Thompson (2009) and Marshall and Jonker (2011) on inferential statistics). Insights about statistical significance of model performance is enriched by descriptive statistics of the experimental results (see, for example, Jargowsky and Yang (2005) on descriptive statistics).

It is generally acknowledged that there are two different types of inferential statistics, that is, parametric inferential statistics and non-parametric inferential statistics. There is a wide agreement that parametric inferential statistics should be used as long as particular assumptions are met. When the assumptions are not met, non-parametric inferential statistics should be employed (see, for instance, Allua and Thompson (2009) and Marshall and Jonker (2011)).

With respect to its purpose, inferential statistics can be divided into three categories: evaluating differences, studying relationships, and establishing predictions. The current research tries, among others, to obtain inferences about the performance of the models and whether the information accuracy on resource availability affects the performance of model III and model IV. The performance of the models is evaluated with regard to their maximum objective value. The inferential statistical test methods carried out in chapters 4 and 5 are, therefore, those which fall into the classification of difference evaluation.

Considering the characteristics of the data to be tested, one-way analysis of variance (ANOVA), Tukey test, Kruskal-Wallis test and Mann-Whitney test are chosen as testing methods. One-way ANOVA or Kruskal-Wallis is intended to provide general insights on model performance and effect of resource information accuracy. Tukey test or Mann-Whitney test, in the meantime, aims to find out which model(s) and level(s) of information accuracy differ(s) from others when it is found from previous evaluation that model performances differ or accuracy on resource information affects model performance.

In conducting an ANOVA test, several assumptions should be met. Some of the assumptions are related to the error terms or residuals, i.e. they should (Higgins, 2004): (1) be normally distributed, (2) have zero means, (3) have equal variances (in other words, be homoscedastic) and (4) be mutually uncorrelated (in other words, their covariance equals 0).

The statistical data processing with a predetermined value of α is conducted as follows.

1. Firstly, conduct a one-way ANOVA and a Tukey test to the data under concern. Produce a plot of residuals versus order.
2. A normality test to the residuals produced by the ANOVA test is subsequently applied.
3. If the normality test suggests that the residuals are normally distributed, do an equality of variance test. Otherwise, go to step 7 onwards.
4. If the equality of variance test indicates that the residuals have equal variances, do a 1-sample *t* test on residuals in order to see whether the residuals have zero mean. Otherwise, go to step 7 onwards.
5. If it is indicated that the residuals have zero mean, check the plot of the residuals versus order. Otherwise, go to step 7 onwards.
6. If the plot of the residuals versus order suggests that the related residuals are mutually uncorrelated, stop, and the ANOVA test and Tukey test results are analysed. The analysis on the ANOVA test results will tell whether the levels of factor under study are different from each other. If this is the case, which level of factor differ from which other levels can be obtained by analysing the Tukey test results. When the ANOVA test results indicate that there is no difference among levels of factor, then the Tukey test results will not tell any important insights.

7. If the plot of the residuals versus order indicates that the related residuals are mutually correlated, go to step 8 onwards.
8. Apply a Kruskal-Wallis test on the data under concern.
9. From the Kruskal-Wallis test, two possibilities emerge: (1) the levels of factor under study differ from each other, or (2) there is no difference on the levels of factor under concern. If alternative (1) is the case, apply Mann-Whitney test to pairs of factor level. Otherwise, stop.
10. The Mann-Whitney test is carried out by using a new value of α proposed by Bonferroni (Higgins, 2004), as follows:

$$\propto' = \frac{\propto}{\left(\frac{k(k-1)}{2}\right)}$$

Where:
$\propto'$ = new value of α; and
k = the total number of levels of factor under consideration

In processing the data, Minitab 16 - a statistical software package – is used. The alpha value for the data processing is set to 0.05. This value of alpha simply means that the level of confidence is set to 0.95. In words, this means that the probability of deducing a conclusion that is really true is 95 percent.

In doing ANOVA tests, Tukey tests, Kruskal-Wallis tests and Mann-Whitney tests by using Minitab, many outputs and indicators can be produced. In this thesis, however, only the most relevant outputs of the aforementioned tests are presented.

Outputs from the Kruskal-Wallis test provided in the test results are *P* value, average rank of each of the models and median of each of the models. With regard to the Mann-Whitney test, outputs presented are *P* value of the pairwise comparison and median values of each of the models. Because the median values in the two tests are identical, they are only provided once. The output of the ANOVA test presented in this thesis, meanwhile, is the *P* value. Finally, the output from the Tukey test that is provided in this thesis is the grouping level of factor.

From the abovementioned results on the four tests on residuals, two conditions emerge and need further action. The results from ANOVA and Tukey tests on data of which residuals are normally distributed, have equal variances, have zero mean and are mutually uncorrelated proceed to analysis and discussion. Other data, on the other hand, go to further data processing by the already-determined non-parametric inferential statistics (i.e. Kruskal-Wallis test and Mann-Whitney test).

Note on Effect Size Calculation

The calculation of effect sizes in the thesis is performed by following Durlak (2009) on Cohen's effect size d. By using the following notations:

d = Cohen's effect size
M_E = mean of intervention group;
M_C = mean of control group;
N = total sample size;
SD_E = standard deviation of intervention group;
SD_C = standard deviation of control group;

Then the Cohen's effect size d is calculated as follows:

$$d = \frac{M_E - M_C}{\text{Sample SD pooled}} \times \left(\frac{N-3}{N-2.25}\right) \times \sqrt{\frac{N-2}{N}}$$

Where sample SD pooled is calculated as follows:

$$\text{Sample SD pooled} = \sqrt{\frac{[{SD_E}^2 + {SD_C}^2]}{2}}$$

Because the maximum objective values in the thesis is "the smaller the better", the implementation of this effect size d needs a slight modification. For instance, if we want to calculate the effect size of model IV relative to model II with regard to redcomb (see Table F.6 of Appendix F),then the M_E represents the mean value of model II and the M_C represents the mean value of model IV. The effect size d is then calculated using the above formula.

Appendix C Summary of Tests on Assumption with Respect to Residuals - Original Data

Normality Test on Residuals

As has already been stated in the preceding parts of the thesis, parametric inferential statistical methods are used whenever possible. In applying the parametric inferential methods, however, particular assumptions need to be met. One of the conditions is that the variables of data population are normally distributed. With respect to samples of the population, it simply means that the residuals of the model of the samples need to be normally distributed. With this motivation, normality tests on residuals are carried out.

The normality tests are performed by firstly determining a null hypothesis (and its counterpart, an alternative hypothesis). Regarding this, the null hypothesis (which is usually represented by symbol H_0) is that the related variable under study has a normal distribution. The alternative hypothesis, in the meantime, is that the variable has a distribution other than normal.

Each normality test performed in this study ends up with a probability plot graph. The graph contains information one of which is a P value. Using a specific value of a predetermined alpha (that is, the probability of rejecting H_0 where, in reality, the H_0 holds), the P figure can then be used to conclude whether the residual-related variable under study has a normal distribution or not. The tested variable is normally distributed if the resultant P value is greater than or equal to the predetermined alpha figure. Given an alpha figure of 0.05, for instance, a normality test on residuals of a particular variable which gives P value greater than or equal to 0.05 merely means that the variable has a normal distribution. If the resulting P value is less than 0.05, then it is concluded that the variable does not follow a normal distribution.

Normality tests on residuals in the thesis are performed by carrying out the following two stages. Firstly, the data under consideration are tested by applying one-way-analysis of variance (one-way ANOVA). Secondly, a normality test on residuals resulting from the one-way ANOVA test is conducted.

Equality of Variance Test on Residuals

The residuals with normal distribution are further tested with regard to the equality of their variances. The test is performed by using Minitab 16 and by setting the alpha value to 0.05. A P value greater than or equal to 0.05 indicates that the variances of the variables under concern are equal. Conversely, inequality among variances exists if the resulting P value is less than 0.05.

Zero-Mean Test on Residuals

The zero-mean test is applied to the residuals that are normally distributed and have equal variances. This is performed by carrying out a 1-sample t test on the related data. Suggestion that the means of the variables under concern equal zero is provided if the resultant P value is greater than or equal to 0.05. If, in contrast, the resultant P value is less than 0.05, the related means are suggested to be other than zero.

Correlation of Residuals

The presence of correlation in the residuals can be detected by observing the plot of the residuals versus order.

By following the above mentioned guidelines, the assumptions are tested. What follows are the results of the tests.

Appendix C.1 Summary of tests on original data with regard to models

No.	Data	P value, distribution	P value, equality of variance	P value, mean=0 or not
1.	NT11R3Na9_0%	0.068, not normal	0.001, not equal	-
2.	NT11R3Na9_5%	0.034, not normal	-	-
3.	NT11R3Na9_25%	0.044, not normal	-	-
4.	NT16R3Na9_0%	<0.005, not normal	-	-
5.	NT16R3Na9_5%	<0.005, not normal	-	-
6.	NT16R3Na9_25%	<0.005, not normal	-	-
7.	NT11R17Na47_0%	<0.005, not normal	-	-
8.	NT11R17Na47_5%	<0.005, not normal	-	-
9.	NT11R17Na47_25%	<0.005, not normal	-	-
10.	NT16R17Na47_0%	<0.005, not normal	-	-
11.	NT16R17Na47_5%	<0.005, not normal	-	-
12.	NT16R17Na47_25%	<0.005, not normal	-	-

Appendix C.2 Summary of tests on original data with regard to information deviation in model III

No.	Data	P value, distribution	P value, equality of variance	P value, mean=0 or not
1.	NT11R3Na9	0.032, not normal	-	-
2.	NT16R3Na9	0.008, not normal	-	-
3.	NT11R17Na47	0.297, normal	0.964, equal	1.000, yes
4.	NT16R17Na47	0.662, normal	0.868, equal	1.000, yes

Appendix C.3 Summary of tests on original data with regard to information deviation in model IV

No.	Data	*P* value, distribution	*P* value, equality of variance	*P* value, mean=0 or not
1.	NT11R3Na9	0.097, normal	0.866, equal	1.000, yes
2.	NT16R3Na9	0.268, normal	0.186, equal	1.000, yes
3.	NT11R17Na47	0.008, not normal	-	-
4.	NT16R17Na47	0.261, normal	0.635, equal	1.000, yes

Appendix C.4 Plot of residuals versus order of original data with regard to information deviation in model III

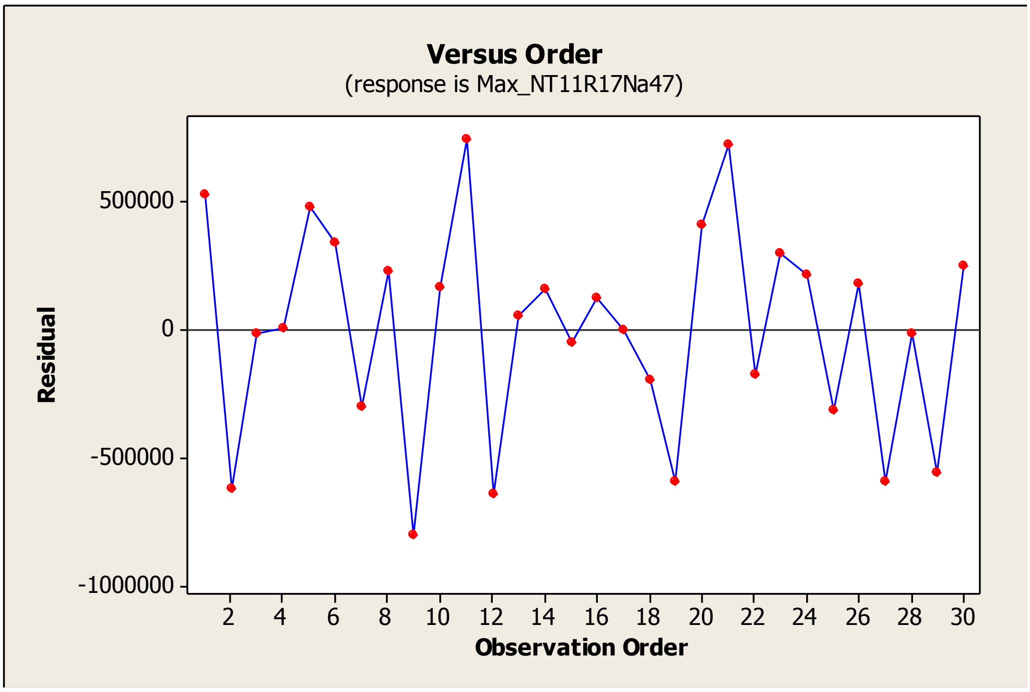


Figure C.4.1 Max_NT11R17Na47

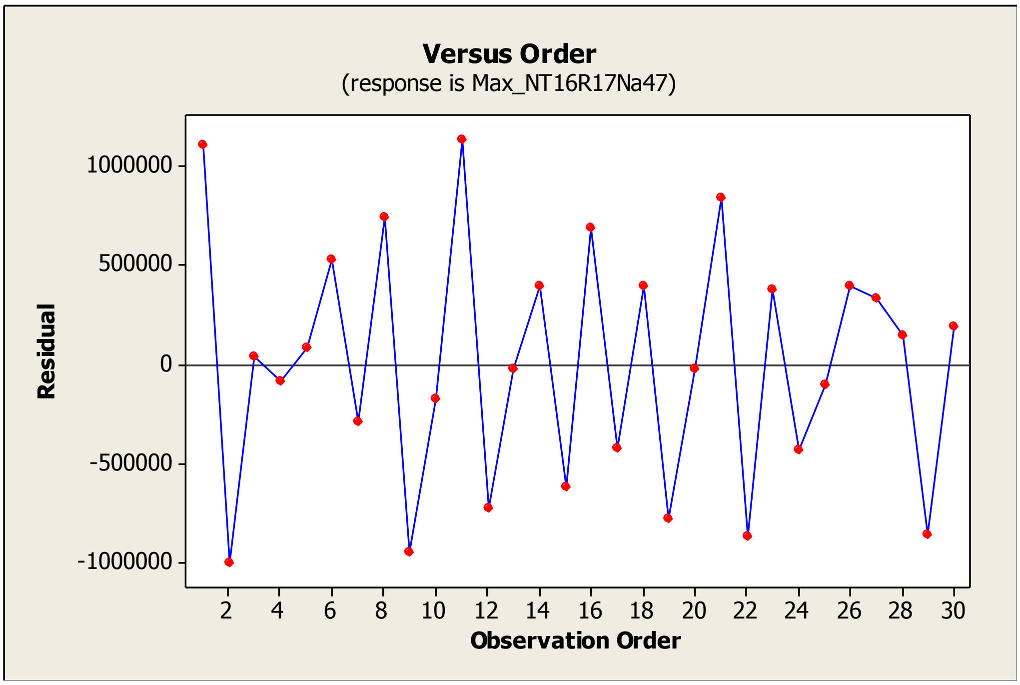


Figure C.4.2 Max_NT16R17Na47

Appendix C.5 Plot of residuals versus order of original data with regard to information deviation in model IV

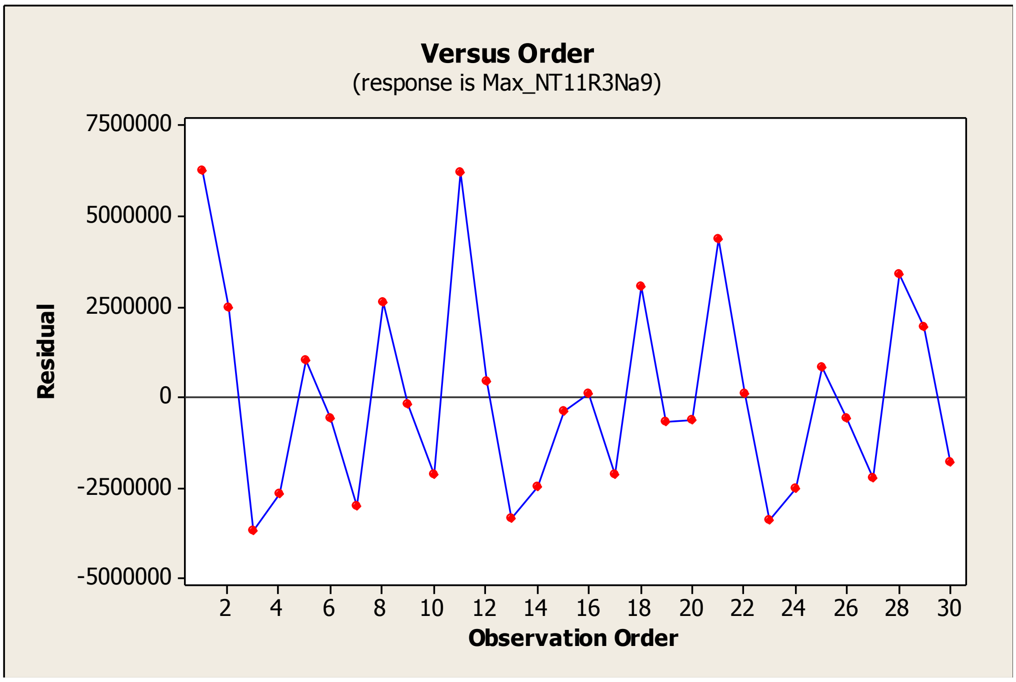


Figure C.5.1 Max_NT11R3Na9

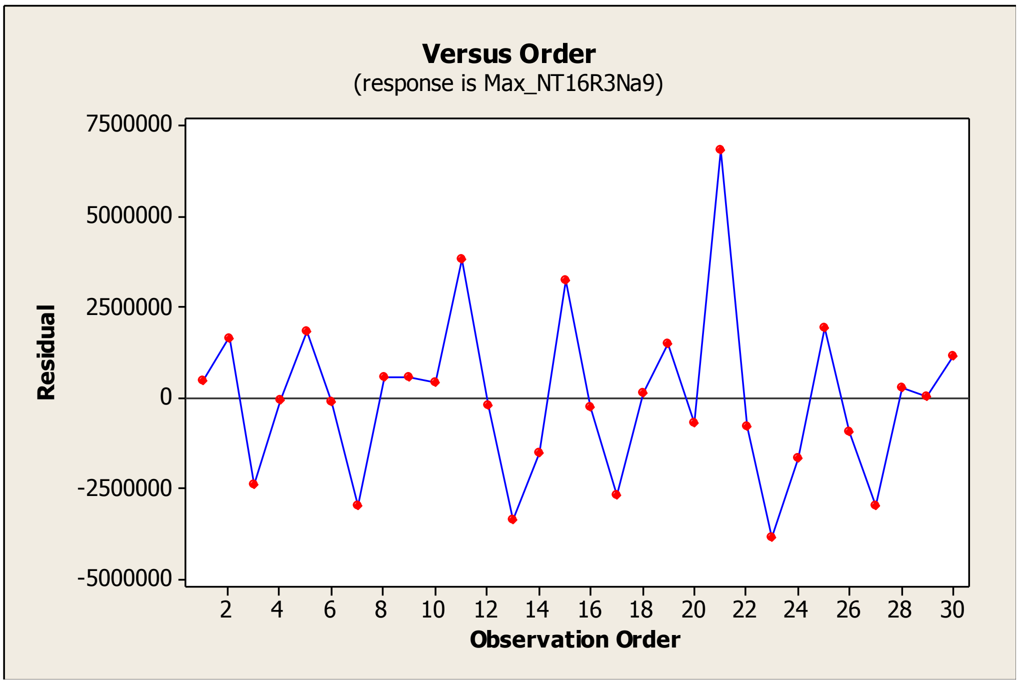


Figure C.5.2 Max_NT16R3Na9

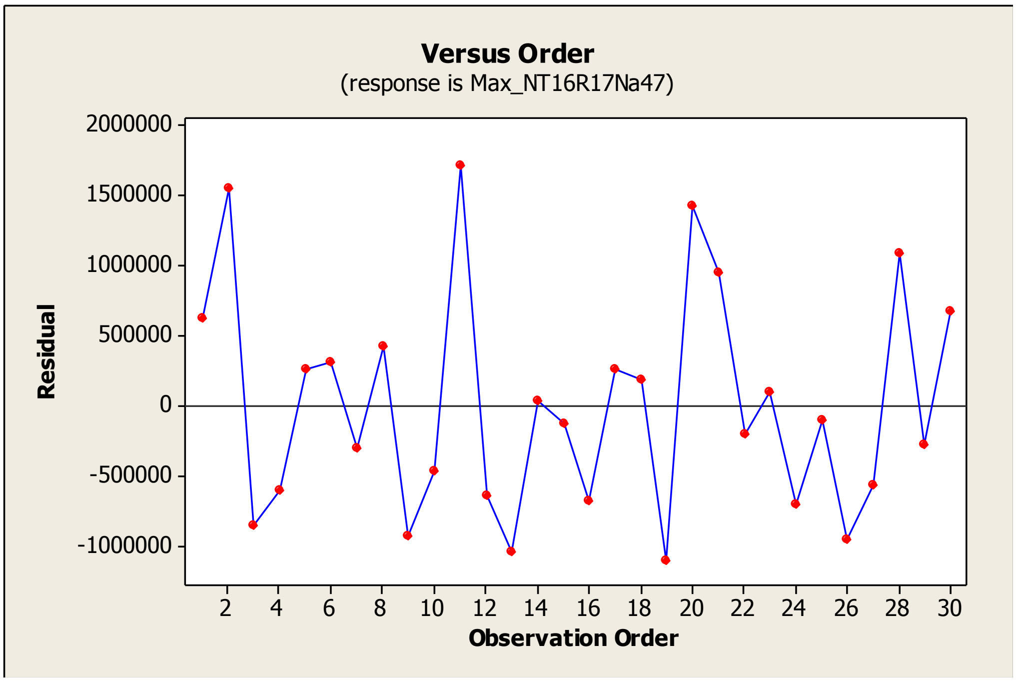


Figure C.5.3 Max_NT16R17Na47

Appendix D Suffering Reduction – Original Data

Table D.1 Suffering reduction NT11R3Na9_0%

Dataset	Suffering reduction NT11R3Na9_0%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	180,227	90,086	224,621	117,195	174,913	82,490
2	149,577	32,198	151,384	127,934	129,904	2,930
3	314,452	243,868	319,081	188,177	200,518	23,834
4	252,943	146,340	285,006	170,564	221,863	91,128
5	99,916	-60,632	48,517	138,958	94,471	-69,088
6	223,789	47,144	218,344	200,917	194,724	-12,766
7	234,716	116,096	276,834	168,853	228,806	105,679
8	306,395	50,622	282,981	293,897	266,992	-108,969
9	300,554	177,357	321,839	225,833	264,849	92,607
10	350,635	224,559	353,919	296,949	304,684	32,355
Average	241,320	106,764	248,252	192,928	208,172	24,020
StdDev	80,050	94,208	91,713	63,365	64,117	72,662

Table D.2 Suffering reduction NT11R3Na9_5%

Dataset	Suffering reduction NT11R3Na9_5%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	180,227	63,934	228,720	139,078	197,072	90,106
2	149,577	50,167	219,708	114,074	194,550	113,717
3	314,452	242,910	314,498	189,490	189,612	237
4	252,943	133,450	285,162	181,591	230,552	91,572
5	99,916	9,538	133,763	92,642	127,337	45,495
6	223,789	43,940	202,112	202,668	178,241	-50,819
7	234,716	79,616	245,155	194,853	207,968	26,194
8	306,395	38,828	280,343	297,130	268,200	-121,245
9	300,554	185,886	331,072	218,971	277,247	132,780
10	350,635	203,716	340,134	307,374	285,405	-103,449
Average	241,320	105,199	258,067	193,787	215,618	22,459
StdDev	80,050	80,742	64,603	69,953	49,855	89,916

Table D.3 Suffering reduction NT11R3Na9_25%

Dataset	Suffering reduction NT11R3Na9_25%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	180,227	70,028	258,432	134,299	229,606	145,316
2	149,577	14,586	237,280	140,232	231,341	142,211
3	314,452	245,434	326,050	185,992	217,246	59,714
4	252,943	143,842	298,400	172,791	244,783	129,198
5	99,916	-50,381	84,164	133,112	119,161	-21,173
6	223,789	43,434	235,764	202,942	216,416	28,074
7	234,716	163,169	260,177	122,957	166,714	63,886
8	306,395	71,465	279,321	287,597	254,454	-126,001
9	300,554	213,800	299,672	191,874	189,922	-3,840
10	350,635	211,457	355,510	303,786	314,427	48,030
Average	241,320	112,683	263,477	187,558	218,407	46,541
StdDev	80,050	97,553	73,643	63,427	52,542	83,966

Table D.4 Suffering reduction NT16R3Na9_0%

Dataset	Suffering reduction NT16R3Na9_0%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	328,270	146,075	344,373	291,193	316,928	101,391
2	256,308	17,007	282,941	250,205	278,051	77,598
3	321,205	248,357	341,501	200,356	256,178	114,719
4	263,232	166,579	244,012	168,637	135,102	-59,054
5	134,981	90,736	175,888	57,649	110,949	62,538
6	318,730	91,411	302,885	296,853	276,162	-86,460
7	310,609	97,146	347,147	284,213	332,862	179,047
8	350,323	120,337	355,936	332,524	340,639	54,866
9	352,568	250,533	359,011	285,003	303,000	66,732
10	357,390	305,991	361,652	238,064	257,802	50,615
Average	299,362	153,417	311,535	240,470	260,767	56,199
StdDev	67,322	89,810	61,313	80,564	78,399	78,056

Table D.5 Suffering reduction NT16R3Na9_5%

Dataset	Suffering reduction NT16R3Na9_5%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	328,270	187,625	309,074	270,881	233,910	-120,873
2	256,308	18,380	309,993	249,688	306,026	156,416
3	321,205	220,301	357,880	231,706	315,922	207,297
4	263,232	113,886	282,681	210,890	238,354	59,757
5	134,981	68,958	114,119	80,194	54,855	-31,893
6	318,730	69,843	299,449	303,140	279,657	-105,206
7	310,609	97,524	324,978	284,077	303,233	70,413
8	350,323	129,274	356,355	330,547	339,566	58,955
9	352,568	249,565	350,883	285,727	281,053	-17,452
10	357,390	308,226	366,291	233,917	276,265	105,712
Average	299,362	146,358	307,170	248,077	262,884	38,313
StdDev	67,322	91,880	73,525	69,206	80,063	106,947

Table D.6 Suffering reduction NT16R3Na9_25%

Dataset	Suffering reduction NT16R3Na9_25%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	328,270	148,244	272,784	290,305	200,830	-349,378
2	256,308	10,621	306,180	252,561	303,828	145,307
3	321,205	255,475	349,742	190,327	272,961	161,303
4	263,232	178,772	260,625	155,860	151,049	-8,010
5	134,981	176,353	131,966	-75,482	-80,983	-4,609
6	318,730	77,893	296,570	300,895	273,209	-120,919
7	310,609	115,581	308,411	277,097	273,974	-10,768
8	350,323	118,677	349,721	332,877	332,011	-5,886
9	352,568	244,187	355,281	289,575	296,825	28,101
10	357,390	296,511	350,434	253,455	224,496	-82,616
Average	299,362	162,231	298,172	226,747	224,820	-24,747
StdDev	67,322	87,103	67,626	118,489	119,965	143,583

Table D.7 Suffering reduction NT11R17Na47_0%

Dataset	Suffering reduction NT11R17Na47_0%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	322,605	311,817	300,887	53,679	-54,386	-125,300
2	289,940	276,732	273,531	45,409	-11,004	-63,841
3	206,705	181,401	236,923	47,282	103,747	64,250
4	199,551	164,513	292,930	60,573	222,006	191,094
5	240,753	119,140	272,703	175,057	221,047	83,402
6	291,190	145,948	251,331	232,012	168,340	-157,030
7	261,955	237,285	268,843	62,939	80,512	20,953
8	326,545	340,051	346,451	-105,005	49,760	121,951
9	244,111	338,222	301,589	-705,944	-274,796	153,490
10	292,346	294,329	267,984	-8,066	-107,184	-97,110
Average	267,570	240,944	281,317	-14,207	39,804	19,186
StdDev	44,486	82,798	30,749	259,639	156,505	123,223

Table D.8 Suffering reduction NT11R17Na47_5%

Dataset	Suffering reduction NT11R17Na47_5%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	322,605	308,915	284,760	65,689	-115,901	-218,343
2	289,940	290,306	250,250	-1,429	-156,412	-154,417
3	206,705	187,645	249,203	36,712	118,571	90,359
4	199,551	161,160	233,968	65,398	124,028	70,433
5	240,753	195,416	202,145	90,810	13,479	-100,784
6	291,190	184,233	216,791	202,606	61,673	-293,105
7	261,955	219,962	240,325	96,236	46,665	-65,797
8	326,545	353,285	340,255	-282,319	-137,568	83,990
9	244,111	334,282	297,620	-628,761	-255,640	142,893
10	292,346	288,717	216,106	13,949	-279,095	-303,907
Average	267,570	252,392	253,142	-34,111	-58,020	-74,868
StdDev	44,486	70,155	42,709	243,151	149,818	166,273

Table D.9 Suffering reduction NT11R17Na47_25%

Dataset	Suffering reduction NT11R17Na47_25%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	322,605	307,346	275,937	71,831	-147,854	-269,242
2	289,940	240,559	323,420	128,740	216,023	130,253
3	206,705	152,926	259,889	88,433	175,888	113,080
4	199,551	146,244	181,049	85,257	55,667	-37,862
5	240,753	218,756	109,416	50,058	-248,814	-342,851
6	291,190	170,627	179,614	214,231	15,970	-439,566
7	261,955	272,117	332,838	-33,570	200,593	215,615
8	326,545	347,336	338,952	-189,081	-76,244	76,009
9	244,111	329,268	312,002	-544,973	-110,493	181,299
10	292,346	293,282	229,940	-3,768	-254,930	-248,761
Average	267,570	247,846	254,306	-13,284	-17,419	-62,203
StdDev	44,486	73,724	77,795	215,341	177,932	241,010

Table D.10 Suffering reduction NT16R17Na47_0%

Dataset	Suffering reduction NT16R17Na47_0%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	289,635	317,583	307,933	-150,098	-51,825	70,974
2	233,881	322,524	52,921	-510,789	-1,553,547	-451,628
3	142,336	159,145	162,055	-28,385	4,913	31,040
4	191,884	153,773	107,356	62,893	-76,601	-166,293
5	177,719	226,278	137,832	-115,570	-210,502	-73,242
6	141,198	233,119	190,398	-228,297	-106,104	77,093
7	175,913	272,857	208,107	-322,275	-215,249	58,618
8	356,769	358,351	351,524	-19,361	-83,529	-61,135
9	314,279	361,893	334,362	-655,327	-378,919	103,166
10	334,864	346,679	331,610	-105,826	-134,972	-22,928
Average	235,848	275,220	218,410	-207,303	-280,634	-43,434
StdDev	81,705	78,851	106,600	228,233	460,098	166,135

Table D.11 Suffering reduction NT16R17Na47_5%

Dataset	Suffering reduction NT16R17Na47_5%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	289,635	318,167	284,030	-154,472	-184,817	-21,740
2	233,881	304,628	235,415	-322,459	-315,470	3,827
3	142,336	172,436	199,597	-53,931	48,663	90,137
4	191,884	97,017	37,143	126,254	-79,683	-304,427
5	177,719	289,467	180,759	-432,716	-420,944	5,582
6	141,198	225,934	262,731	-201,248	87,395	190,436
7	175,913	286,039	174,637	-412,410	-417,189	-2,324
8	356,769	363,152	355,970	-91,928	-103,439	-9,316
9	314,279	357,980	343,642	-528,537	-173,416	150,835
10	334,864	343,832	285,521	-75,398	-490,265	-347,691
Average	235,848	275,865	235,944	-214,684	-204,916	-24,468
StdDev	81,705	86,322	93,773	204,697	200,693	174,907

Table D.12 Suffering reduction NT16R17Na47_25%

Dataset	Suffering reduction NT16R17Na47_25%					
	M_II to M_I	M_III to M_I	M_IV to M_I	M_II to M_III	M_IV to M_III	M_IV to M_II
1	289,635	325,874	309,352	-219,688	-100,162	76,475
2	233,881	317,977	221,458	-454,104	-521,188	-31,006
3	142,336	126,850	92,970	22,944	-50,196	-77,709
4	191,884	209,939	172,010	-39,078	-82,091	-39,097
5	177,719	247,621	200,342	-191,261	-129,362	41,540
6	141,198	246,559	298,649	-286,153	141,474	246,718
7	175,913	231,209	257,250	-135,686	63,900	148,095
8	356,769	366,571	348,073	-161,567	-304,900	-101,366
9	314,279	361,496	325,997	-640,884	-481,832	60,195
10	334,864	339,084	311,872	-32,188	-207,564	-162,012
Average	235,848	277,318	253,797	-213,767	-167,192	16,183
StdDev	81,705	77,469	80,995	203,937	216,137	123,122

Appendix E Detailed Analysis and Discussion on Experimental Results

E.1 Model Performance Comparison

In order to check the statistical significance of the model performance, Kruskal-Wallis and Mann Whitney tests are performed. Results of these two tests are summarised in Tables E.1 and E.2. Practical significance of model performance, on the other hand, is presented as model effect sizes and suffering reduction. The effect sizes of various problem sizes with regard to models are presented in Table E.3. Tables E.4 and E.5, in the meantime, present averages and standard deviations of the suffering reductions relating to the models. Several figures in reference to data on suffering reduction (see Figures E.1-E.13 of this Appendix) are also produced to assist the analysis and discussion.

Table E.1 Kruskal-Wallis and Mann-Whitney tests with respect to models, R3Na9 problems

No.	Problem size	Kruskal-Wallis			Model	P value of Mann-Whitney (α = 0.0083)		
		P value	Average rank	Median		II	III	IV
1.	NT11R3Na9_0%	0.000	30.7	11,876,894	I	0.0013	0.2413	0.0013
			13.3	5,040,569	II		0.0173	0.8501
			25.5	10,688,187	III			0.0113
			12.5	5,000,153	IV			
2.	NT11R3Na9_5%	0.000	30.9	11,876,894	I	0.0013	0.1859	0.0013
			13.6	5,040,569	II		0.0173	0.6776
			25.4	10,437,070	III			0.0091
			12.1	4,662,955	IV			
3.	NT11R3Na9_25%	0.000	31.0	11,876,894	I	0.0013	0.2413	0.0006
			13.8	5,040,569	II		0.0257	0.6776
			25.3	11,029,987	III			0.0113
			11.9	4,676,624	IV			
4.	NT16R3Na9_0%	0.000	32.6	20,206,184	I	0.0002	0.1212	0.0002
			12.4	5,528,420	II		0.0013	0.3847
			27.5	14,126,045	III			0.0003
			9.5	4,748,219	IV			
5.	NT16R3Na9_5%	0.000	32.6	20,206,184	I	0.0002	0.1212	0.0002
			11.2	5,528,420	II		0.0003	0.7337
			27.9	14,460,386	III			0.0004
			10.3	4,408,866	IV			
6.	NT16R3Na9_25%	0.000	32.2	20,206,184	I	0.0002	0.1405	0.0004
			11.6	5,528,420	II		0.0046	0.9698
			26.1	15,232,076	III			0.0046
			12.1	,055,327	IV			

Table E.2 Kruskal-Wallis and Mann-Whitney tests with respect to models, R17Na47 problems

No.	Problem size	Kruskal-Wallis			Model	P value of Mann-Whitney (α = 0.0083)		
		P value	Average rank	Median		II	III	IV
7.	NT11R17Na47_0%	0.000	35.5	4,051,636	I	0.0002	0.0002	0.0002
			15.8	1,579,575	II		0.6232	0.4727
			17.8	1,923,434	III			0.2413
			12.9	1,293,900	IV			
8.	NT11R17Na47_5%	0.000	35.1	4,051,636	I	0.0002	0.0002	0.0006
			14.6	1,579,575	II		0.8501	0.6776
			15.9	1,741,235	III			0.9698
			16.4	1,575,984	IV			
9.	NT11R17Na47_25%	0.000	35.0	4,051,636	I	0.0002	0.0002	0.0008
			14.7	1,579,575	II		0.8501	0.7337
			15.8	1,859,544	III			1.0000
			16.5	1,791,345	IV			
10.	NT16R17Na47_0%	0.000	34.3	5,574,419	I	0.0006	0.0002	0.0013
			18.1	2,483,026	II		0.0452	0.7337
			9.7	1,838,683	III			0.0173
			19.9	2,711,828	IV			
11.	NT16R17Na47_5%	0.000	34.6	5,574,419	I	0.0006	0.0002	0.0006
			18.7	2,483,026	II		0.0452	0.9698
			10.4	1,791,584	III			0.0640
			18.3	2,569,155	IV			
12.	NT16R17Na47_25%	0.000	34.6	5,574,419	I	0.0006	0.0002	0.0008
			19.8	2,483,026	II		0.0257	0.5205
			10.4	1,955,368	III			0.1212
			17.2	2,199,400	IV			

Table E.3 Effect sizes of model on various original problem sizes

No.	Problem size	Relative to model …	Effect size of model …		
			II	III	IV
1.	NT11R3Na9_0%	I	1.36	0.56	1.43
		II		-1.05	0.11
		III			1.14
2.	NT11R3Na9_5%	I	1.36	0.52	1.46
		II		-1.04	0.17
		III			1.18
3.	NT11R3Na9_25%	I	1.36	0.59	1.50
		II		-1.01	0.25
		III			1.22
4.	NT16R3Na9_0%	I	1.52	0.78	1.57
		II		-1.40	0.39
		III			1.49
5.	NT16R3Na9_5%	I	1.52	0.80	1.54
		II		-1.52	0.17
		III			1.55
6.	NT16R3Na9_25%	I	1.52	0.78	1.49
		II		-1.34	-0.15
		III			1.27
7.	NT11R17Na47_0%	I	1.38	1.36	1.43
		II		-0.17	0.23
		III			0.45
8.	NT11R17Na47_5%	I	1.38	1.40	1.31
		II		0.03	-0.25
		III			-0.32
9.	NT11R17Na47_25%	I	1.38	1.38	1.32
		II		-0.08	-0.17
		III			-0.13
10.	NT16R17Na47_0%	I	1.08	1.19	1.06
		II		0.91	-0.14
		III			-1.09
11.	NT16R17Na47_5%	I	1.08	1.19	1.08
		II		0.99	-0.01
		III			-0.89
12.	NT16R17Na47_25%	I	1.08	1.20	1.12
		II		1.07	0.31
		III			-0.80

Table E.4 Averages and standard deviations of suffering reductions on R3Na9 problems with respect to models

Problem size	Average and standard deviation of suffering reduction					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
NT11R3Na9_0%	241,320	106,764	248,252	192,928	208,172	24,020
	80,050	94,208	91,713	63,365	64,117	72,662
NT11R3Na9_5%	241,320	105,199	258,067	193,787	215,618	22,459
	80,050	80,742	64,603	69,953	49,855	89,916
NT11R3Na9_25%	241,320	112,683	263,477	187,558	218,407	46,541
	80,050	97,553	73,643	63,427	52,542	83,966
NT16R3Na9_0%	299,362	153,417	311,535	240,470	260,767	56,199
	67,322	89,810	61,313	80,564	78,399	78,056
NT16R3Na9_5%	299,362	146,358	307,170	248,077	262,884	38,313
	67,322	91,880	73,525	69,206	80,063	106,947
NT16R3Na9_25%	299,362	162,231	298,172	226,747	224,820	-24,747
	67,322	87,103	67,626	118,489	119,965	143,583

Table E.5 Averages and standard deviations of suffering reductions on R17Na47 problems with respect to models

Problem size	Average and standard deviation of suffering reduction					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
NT11R17Na47_0%	267,570	240,944	281,317	-14,207	39,804	19,186
	44,486	82,798	30,749	259,639	156,505	123,223
NT11R17Na47_5%	267,570	252,392	253,142	-34,111	-58,020	-74,868
	44,486	70,155	42,709	243,151	149,818	166,273
NT11R17Na47_25%	267,570	247,846	254,306	-13,284	-17,419	-62,203
	44,486	73,724	77,795	215,341	177,932	241,010
NT16R17Na47_0%	235,848	275,220	218,410	-207,303	-280,634	-43,434
	81,705	78,851	106,600	228,233	460,098	166,135
NT16R17Na47_5%	235,848	275,865	235,944	-214,684	-204,916	-24,468
	81,705	86,322	93,773	204,697	200,693	174,907
NT16R17Na47_25%	235,848	277,318	253,797	-213,767	-167,192	16,183
	81,705	77,469	80,995	203,937	216,137	123,122

The test results presented in the three tables provide a variety of interesting information. In short, Tables E.1 and E.2 show that, statistically speaking, at least one model performs differently from other models. This leads to the necessity to check which model(s) perform(s) differently from which model(s), for which the Mann-Whitney tests are performed. Along with the figures of the effect sizes and the suffering reduction, the Mann-Whitney test results are now examined.

E.1.1 Performance of Model I in Comparison to Other Models

The first interesting result obtained from the Mann-Whitney test is concerned with the performance of model I in comparison with other models within all problem sizes. It is apparent that model II, model III and model IV statistically outperform model I in all of the R17Na47 problems. This insight stems from the fact that the *P* values are much smaller than the alpha value of 0.0083. For all R3Na9 problems, all related *P* values with regard to model I in contrast with model II and model IV are much smaller than 0.0083, suggesting that the performance of model I is statistically surpassed by the performance of model II and model IV. Still relating to R3Na9 problems, the related *P* values of model I and model III - which are higher than 0.0083 – implies that model I performs just as model III.

The statistical insights highlighted above are mostly confirmed by the figures of effect sizes in Table E.3. With regard to R17Na47 problems, all related effect sizes of model I against other models are much larger than 0.8 and hence are of large magnitude. The figures of effect sizes of model I against model II and model IV with respect to R3Na9 problems also give confirmation about the dominance of the performance of model II and model IV over that of model I. Unlike Mann-Whitney tests, effect sizes of model III over model I in R3Na9 problems, on the other hand, suggests that the effect magnitude ranges from around medium to approximately large.

Regarding the reduction of suffering, it is apparent that the application of model II, model III or model IV can extensively reduce the suffering of the victims. The smallest figures of the average values of reduction, around one third of the total amount of the victims of 390,247, are associated with the application of model III to R3Na9 problems. The employment of model II or model III or model IV instead of model I to R17Na47 problems, in the meantime, reduces the suffering up to around two thirds of the total number of victims.

E.1.2 Performance of Models II, III and IV on NT11R3Na9 Problems

Statistically speaking, the performances of all three models are not significantly different from each other for NT11R3Na9 problems. This can be seen by the P values which all fall above the testing P value of 0.0083. Considering the P values resulting from the Mann-Whitney test, model II and model IV seem to perform very closely. Model III, in the meantime, looks to perform a bit worse than model II and model IV.

Practically speaking, nonetheless, the insights are not totally in line with those obtained from the statistical point of view. For example, it is obvious that model II or model IV performs better than that of model III. This is supported by the large value of effect sizes (more than 0.8) and large average value of suffering reduction (around 200,000 victims) of model IV or model II compared to model III. Small average values of suffering reduction in comparison with the standard deviations (see Table E.4) and the fact that the suffering reduction values fluctuate around zero over datasets (see Figures E.1-E.3) give indication that there is no clear dominance of model IV over model II. Fairly small effect sizes of model IV over model II also support the idea that model IV performs roughly the same as model II.

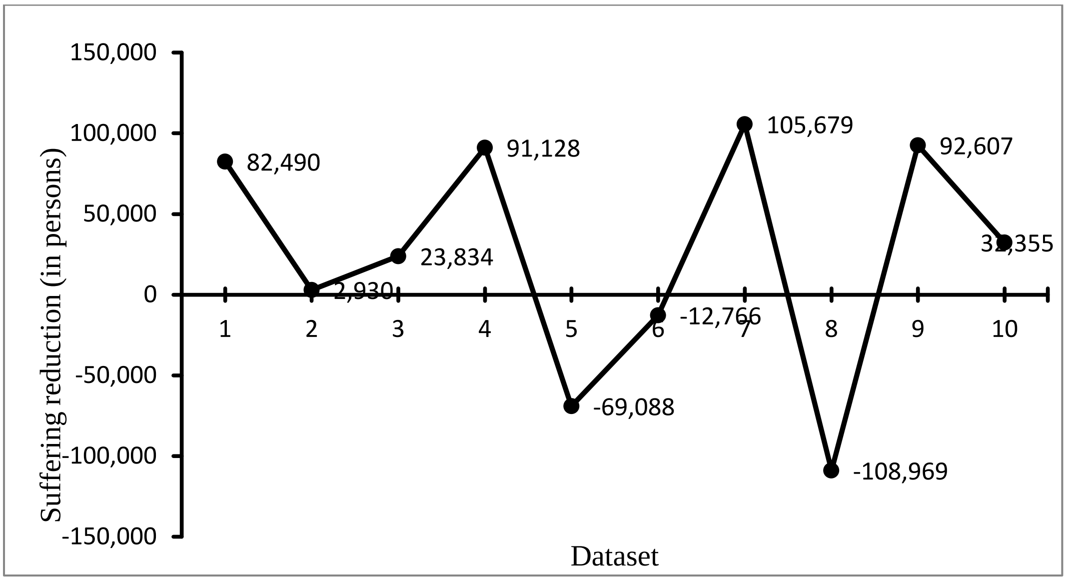


Figure E.1 Suffering reductions of M_IV to M_II – NT11R3Na9_0%

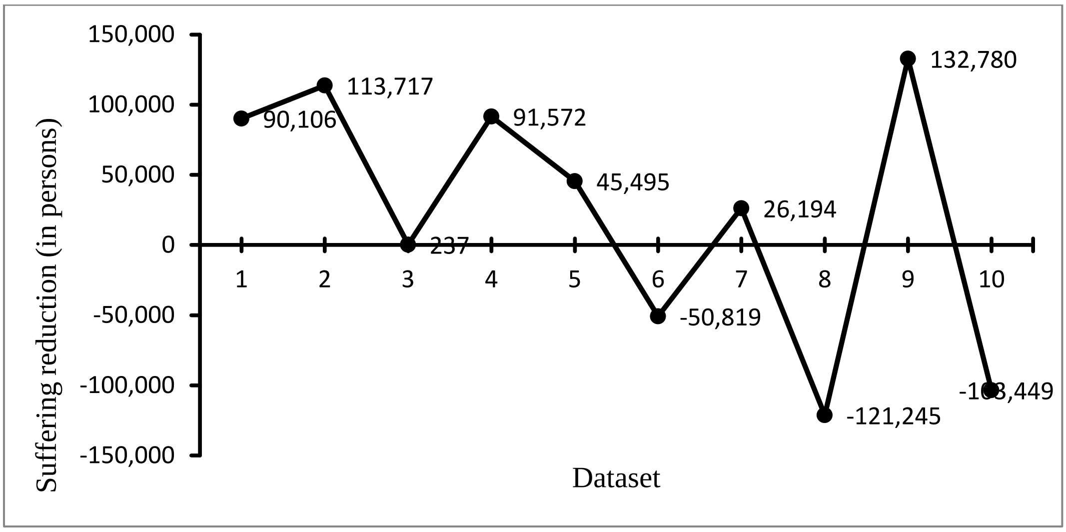


Figure E.2 Suffering reductions of M_IV to M_II – NT11R3Na9_5%

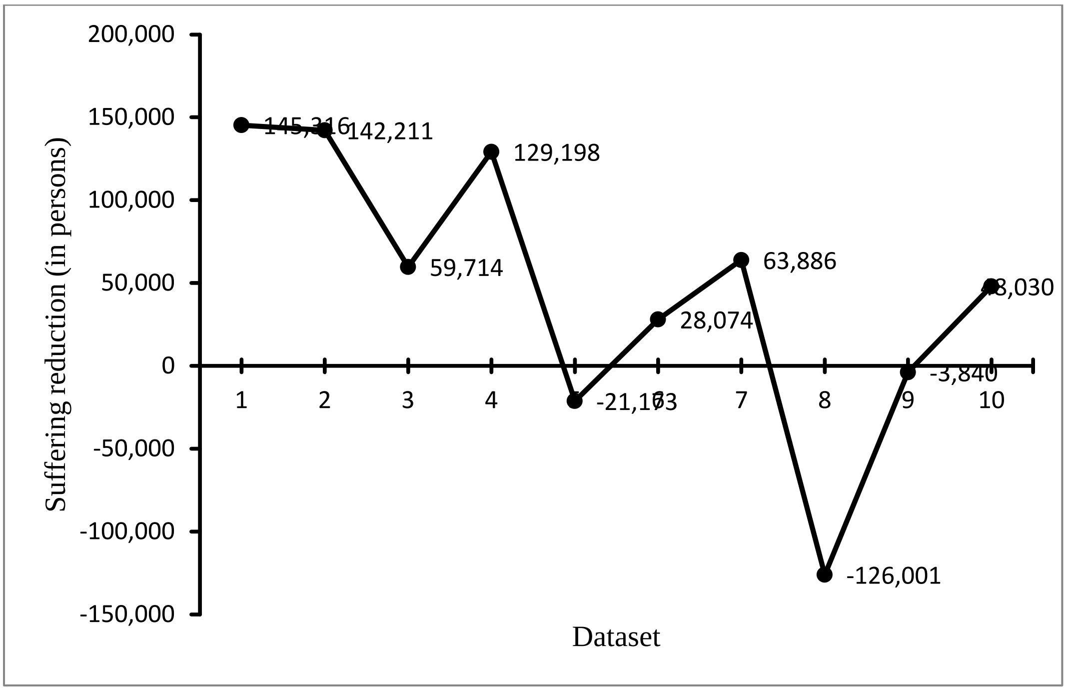


Figure E.3 Suffering reductions of M_IV to M_II – NT11R3Na9_25%

E.1.3 Performance of Models II, III and IV on NT16R3Na9 Problems

Computational experiments related to NT16R3Na9 problems with regard to models II, III and IV provide another interesting comparison of the performance of the related models.

From a statistical point of view, it is obvious that models II and IV perform much better than model III. Regarding model IV and model II solely, *P* values higher than 0.0083 (i.e. the test *P* value) suggest that the two models perform almost the same on NT16R3Na9 problems.

The related effect sizes and average values of suffering reduction suggest similar indication about the performance of model II, model III and model IV with regard to NT16R3Na9 problems. From Tables E.3, E.4 and E.5, it is evident that the application of model II or model IV over model III gives a large effect and reduces suffering of the victims up to around two thirds of the total amount of victims. The same tables, meanwhile, show that the application of model IV over model II to NT16R3Na9_5% problems and NT16R3Na9_25% problems give a small effect (a positive value for NT16R3Na9_5% problems and a negative value for NT16R3Na9_25% problems) with suffering reduction slightly over 38,000 on average (for NT16R3Na9_5% problems) and a little more than -20,000 on average (for NT16R3Na9_25% problems). Relatively small averages in contrast to standard deviation figures and the following graphs (Figures E.4, E.5 and E.6) of suffering reduction over data sets suggest that the performances of model IV and model II for associated problems are comparatively equal. The effect size of 0.39 of model IV over model II with regard to NT16R3Na9_0% problems, on the other hand, proposes caution about the idea of performance similarity between model IV and model II. The caution is supported by the information provided in Figure E.4 wherein 8 out of 10 values of suffering reduction lie above zero, suggesting that the possibility of model IV outperforming model II on NT16R3Na9_0% problems might be worthy of investigation.

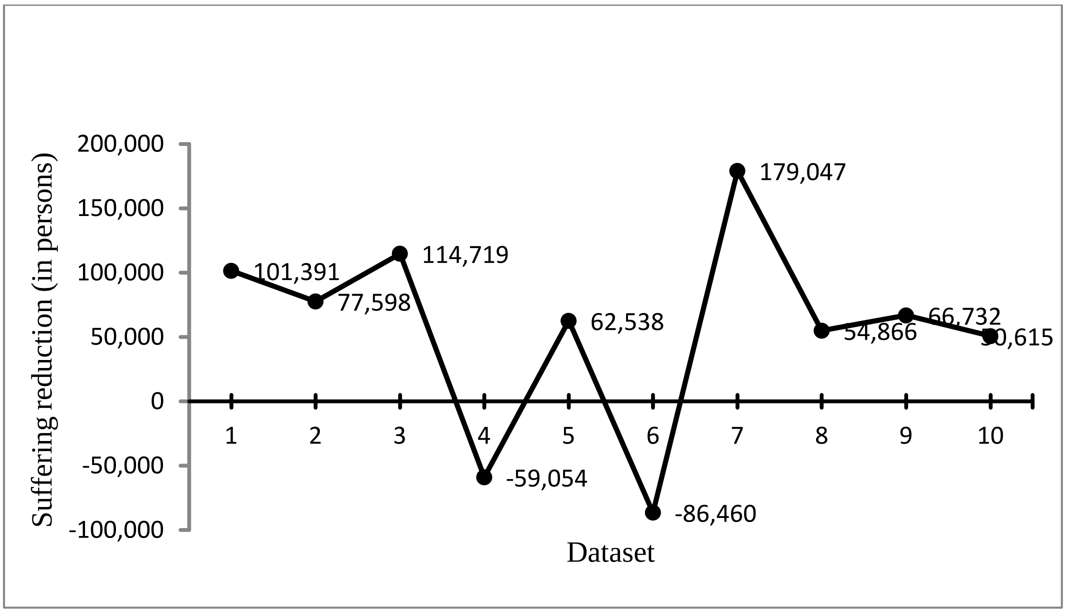


Figure E.4 Suffering reductions of M_IV to M_II – NT16R3Na9_0%

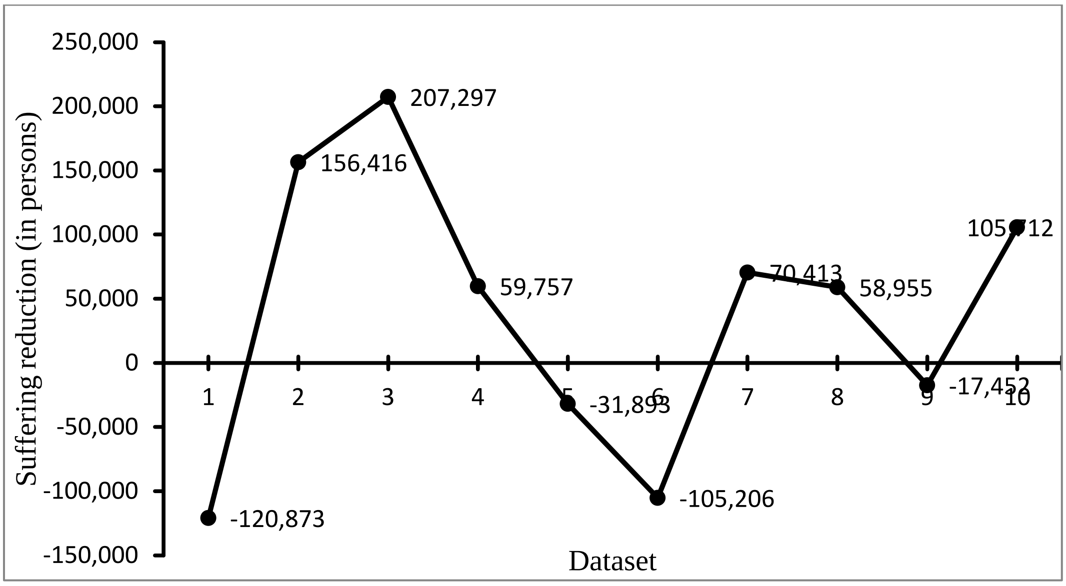


Figure E.5 Suffering reductions of M_IV to M_II – NT16R3Na9_5%

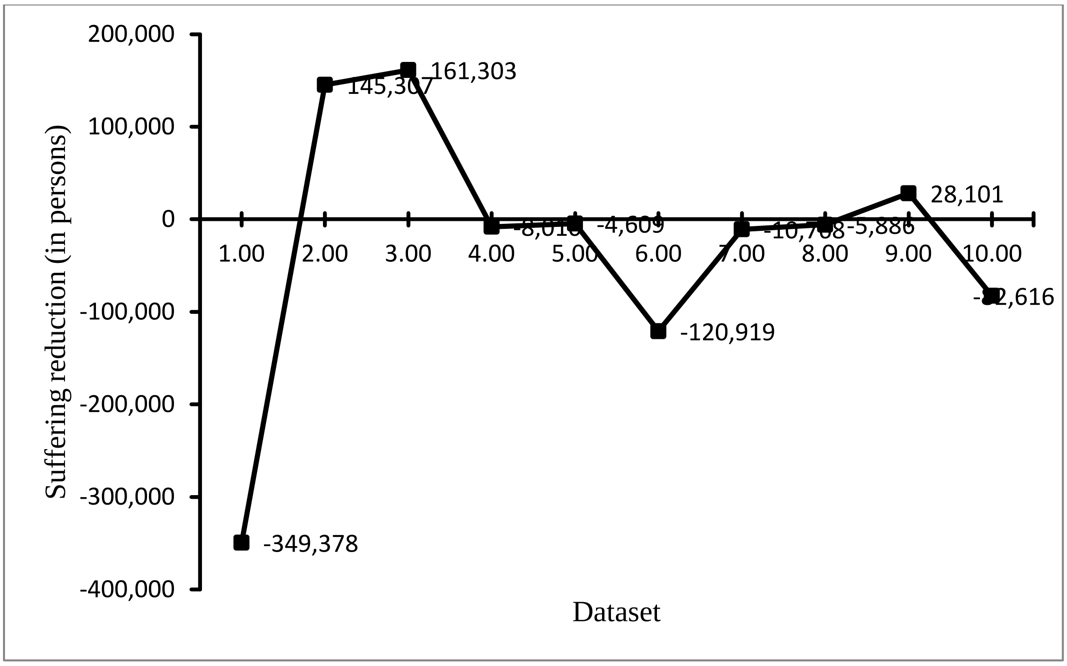


Figure E.6 Suffering reductions of M_IV to M_II – NT16R3Na9_25%

E.1.4 Performance of Models II, III and IV on NT11R17Na47 Problems

Neither the results from Mann-Whitney tests nor the effect size figures provide any indication about which model(s) perform(s) better than (an)other model(s). The related *P* values of the Mann-Whitney tests (see Table E.2) imply that the three models perform relatively the same. Similarly, the small figures of related effect sizes apart from that of model IV to model III on NT11R17Na47_0% problems (see Table E.3) also suggest that the three models under concern have similar performance on NT11R17Na47 problems. Average values of suffering reduction (see Table E.5) and the fluctuation of the suffering reduction around zero – see for example Figures E.7, E.8, E.9 and E.10 – support the performance similarity among the three models on NT11R17Na47 problems.

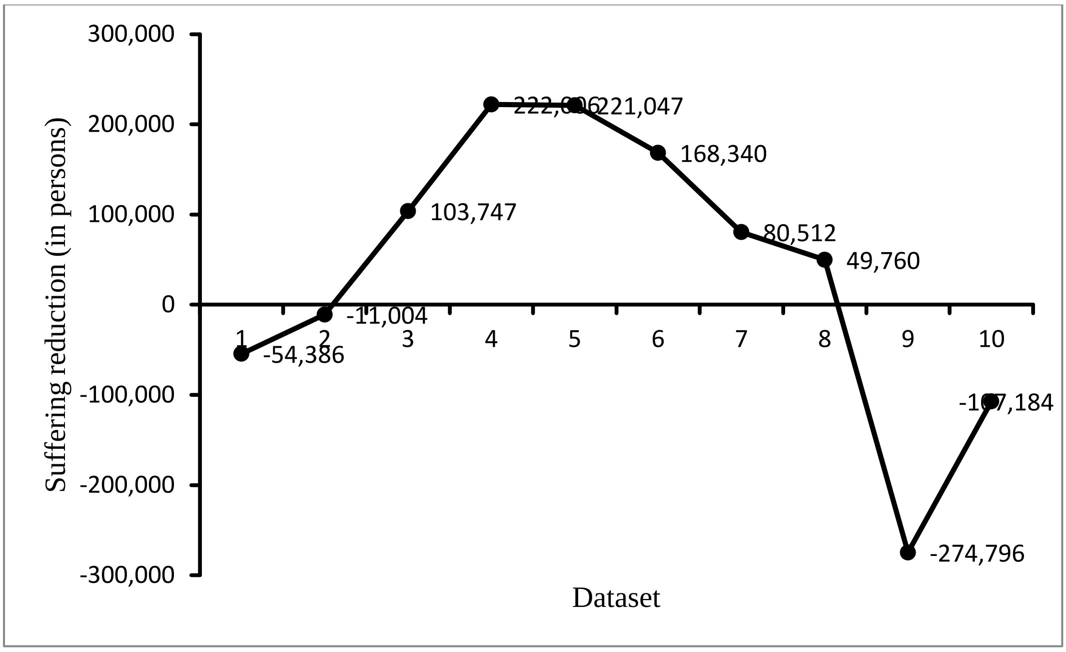


Figure E.7 Suffering reductions of M_IV to M_III – NT11R17Na47_0%

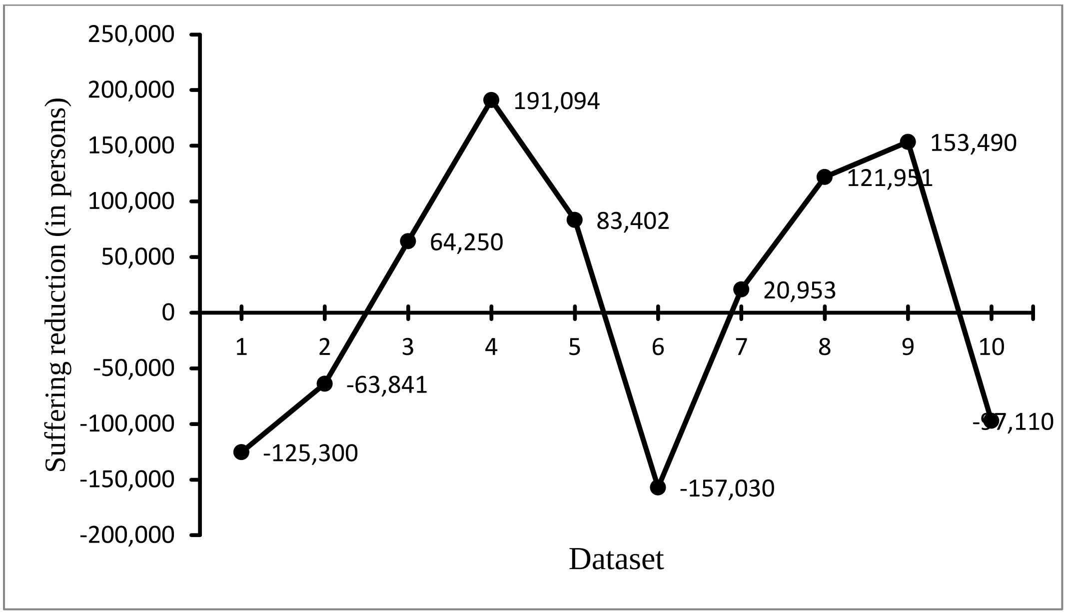


Figure E.8 Suffering reductions of M_IV to M_II – NT11R17Na47_0%

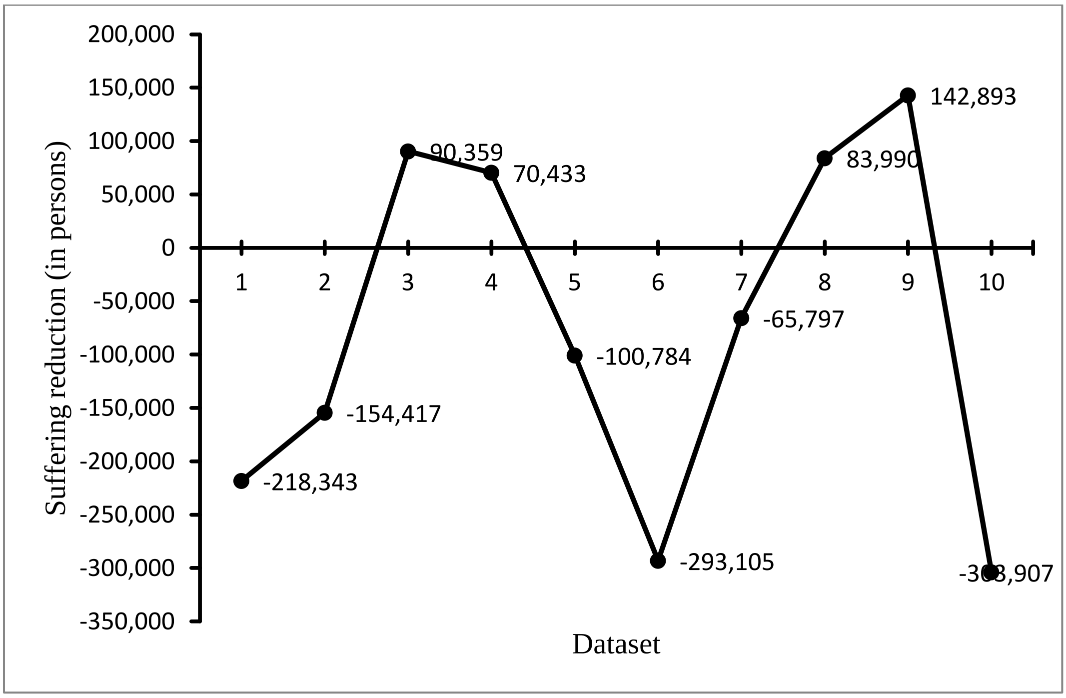


Figure E.9 Suffering reductions of M_IV to M_II – NT11R17Na47_5%

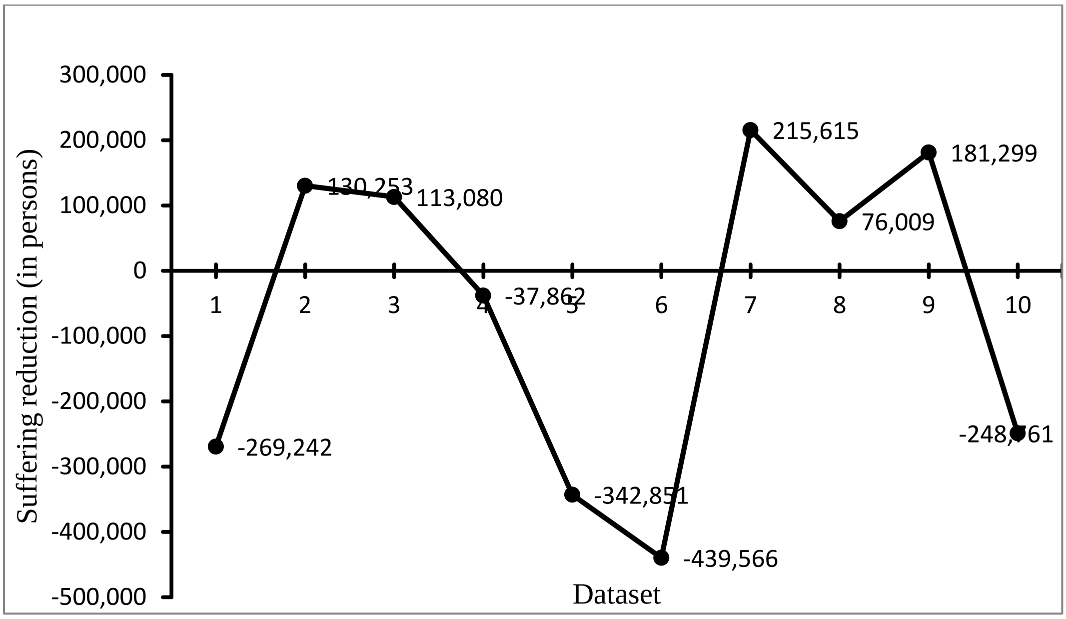


Figure E.10 Suffering reductions of M_IV to M_II – NT11R17Na47_25%

E.1.5 Performance of Model II, III, IV on NT16R17Na47 Problems

Moving from R3Na9 to NT16R17Na47 does mean a large increase in problem size. It is fairly obvious that, glimpsing at the results in Tables E.2, E.3 and E.5, the move to large problems cause changes in the performance pattern of model II, model III and model IV in carrying out relief delivery and injured victim transportation.

Considering the results of the Mann-Whitney tests, the performance of model III looks better than that of models II and IV. This is indicated by the related average rank and median values. The performance difference, however, is not significant from a statistical point of view, as can be seen from the related *P* values (larger than 0.0083).

Effect size and suffering reduction figures for the problems, on the other hand, imply different insights. With respect to the performance of model III over model II and model IV, the effect sizes are larger than 0.8. These figures suggest that model III does better with large magnitude than model II and model IV in minimizing unmet demands of relief supply and victim evacuation. With average figures of suffering reduction of around 200,000 victims, it is unquestionable that model III performance is much better than that of model II and model IV.

With respect to model II and model IV, it seems apparent that the two do not perform significantly differently on NT16R17Na47 problems. The magnitude of effect of model IV to model II adjusts from -0.14 (in NT16R17Na47_0%) to -0.01 (in NT16R17Na47_5%) to 0.31 (in NT16R17Na47_25%). According to the previously mentioned rule of thumb, it can be seen that these last figures are of roughly small size. The average values of suffering reduction provide similar insights to those gained from the effect size figures. The average value of suffering reduction of model IV over model II in contrast to the standard deviation values suggest that the suffering reductions over data sets fluctuate around zero, as is confirmed by Figures E.11–E.13.

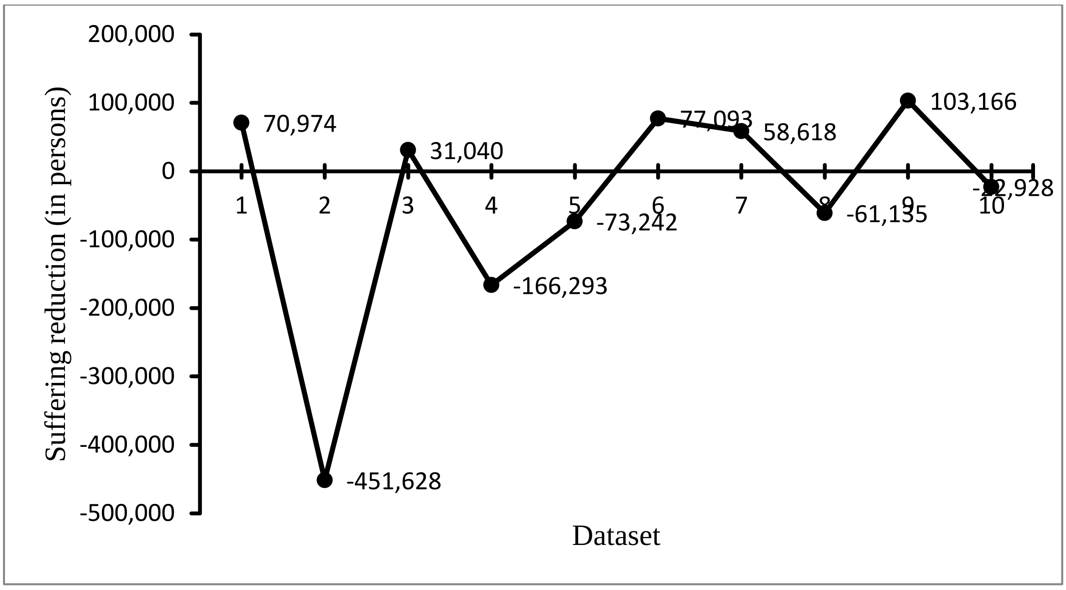


Figure E.11 Suffering reductions of M_IV to M_II – NT16R17Na47_0%

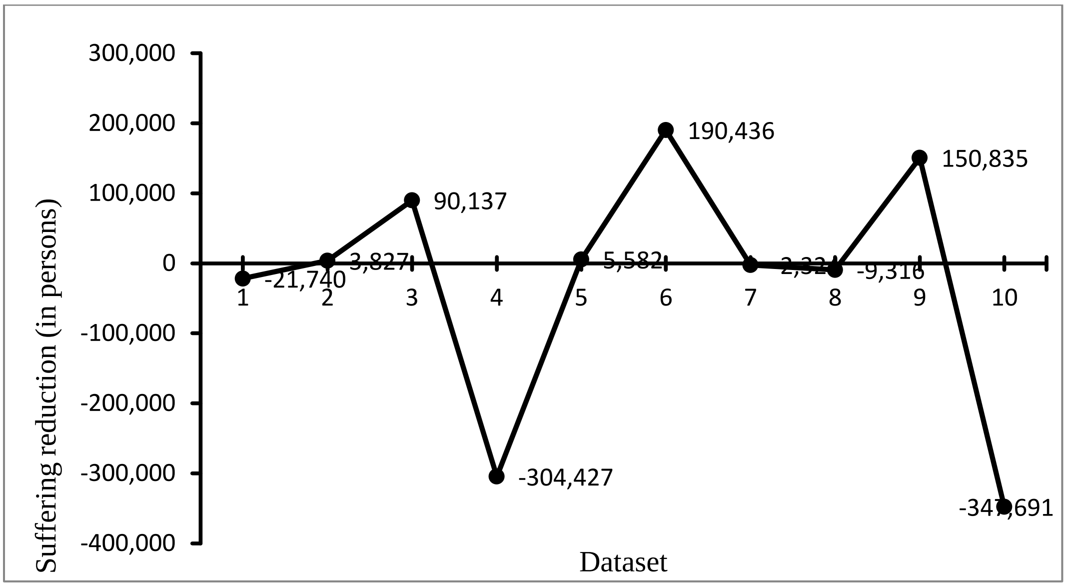


Figure E.12 Suffering reductions of M_IV to M_II – NT16R17Na47_5%

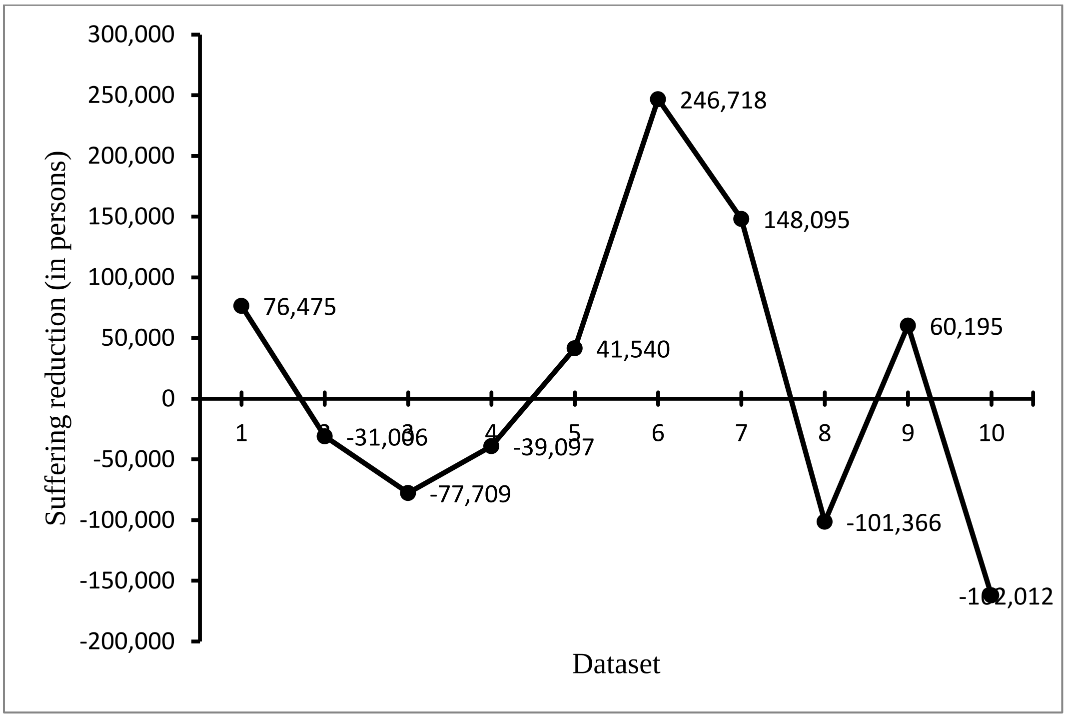


Figure E.13 Suffering reductions of M_IV to M_II – NT16R17Na47_25%

E.2 Comparing the Impact of Information Deviation

In addition to the tests on model performance for a variety of problems, tests that solely examine the impact of information deviation on model performance are also conducted. Approximately half of the related data go to ANOVA and Tukey tests, and the test results are presented in Tables E.6 and E.7 of this appendix. The other half of the related data is tested by Kruskal-Wallis and Mann-Whitney methods, and the test results are provided in Tables E.8 and E.9 of this appendix. Effect sizes of the information deviation in various problems are also calculated and provided in Tables E.10 and E.15. Tables E.11–E.14 and Tables E.16–E.19 of this appendix present suffering reduction results for the problems under concern.

Table E.6 One-way ANOVA and Tukey tests on the effect of information deviation, model III

No.	Problem	ANOVA		Deviation	Tukey's Grouping
		P value	Mean		
1.	NT11R17Na47	0.808	1,838,522	0%	A
			1,713,385	5%	A
			1,778,463	25%	A
2.	NT16R17Na47	0.968	1,861,054	0%	A
			1,816,099	5%	A
			1,790,671	25%	A

Table E.7 One-way ANOVA and Tukey tests on the effect of information deviation, model IV

No.	Problem	ANOVA		Deviation	Tukey's Grouping
		P value	Mean		
1.	NT11R3Na9	0.934	5,403,374	0%	A
			5,186,134	5%	A
			4,931,747	25%	A
2.	NT16R3Na9	0.548	4,289,803	0%	A
			4,636,061	5%	A
			5,430,757	25%	A
3.	NT16R17Na47	0.569	2,735,189	0%	A
			2,618,234	5%	A
			2,350,013	25%	A

Table E.8 Kruskal-Wallis and Mann-Whitney tests on the effect of information deviation, model III

No.	Problem	Kruskal-Wallis			Deviation	*P* value of Mann-Whitney	
		P value	Average rank	Median		5%	25%
1.	NT11R3Na9	0.953	15.2	10,688,187	0%	0.7913	0.9698
			16.2	10,437,070	5%		0.8501
			15.1	11,029,987	25%		
2.	NT16R3Na9	0.988	15.5	14,126,045	0%	0.9698	0.9698
			15.8	14,460,386	5%		0.9097
			15.2	15,232,076	25%		

Table E.9 Kruskal-Wallis and Mann-Whitney tests on the effect of information deviation, model IV

No.	Problem	Kruskal-Wallis			Deviation	*P* value of Mann-Whitney	
		P value	Average rank	Median		5%	25%
1.	NT11R17Na47	0.514	12.9	1,293,900	0%	0.1859	0.5708
			17.1	1,575,984	5%		0.9097
			16.5	1,791,345	25%		

From Tables E.6-E.9 above, it is apparent that all *P* values for either ANOVA tests or Kruskal-Wallis tests are greater than the test *P* value (i.e. 0.05). The lowest *P* value, 0.514, is still very far from 0.05. There is, hence, no strong statistical evidence that model III and model IV perform differently when the maximum value of information deviation varies. In other words, the information deviation allowable in the research has an insignificant effect on model III and model IV performance. From a statistical point of view, therefore, which level of information deviation performs better or worse than other levels does not need to be examined further.

Insights from a practical point of view concerning model III, in the meantime, seem different from those regarding model IV. These two groups of insights, therefore, are presented separately in the following short paragraphs.

E.2.1 Effect of Information Deviation with Respect to Model III

In light of model III, it is obvious from Table E.10 that the (absolute value of the) effect sizes of information deviation on resource availability at the upcoming time points within all problems under study are of small magnitude, from as small as 0.02 to 0.26. This is confirmed by suffering reduction (see Tables E.11–E.14) which, in any problems under discussion, fluctuate around zero and have a smaller average value than that of standard deviation.

Table E.10 Effect size of information deviation with regard to model III

No.	Problem	Deviation	Effect size	
			5%	25%
1.	NT11R3Na9	0%	-0.04	0.03
		5%		0.07
2.	NT16R3Na9	0%	0.02	0.00
		5%		-0.01
3.	NT11R7Na47	0%	0.26	0.13
		5%		-0.14
4.	NT16R7Na47	0%	0.06	0.10
		5%		0.04

Table E.11 Suffering reduction with regard to information deviation concerning model III, NT11R3Na9 problem

Dataset	Suffering reduction_NT11R3Na9_Model III		
	5% to 0%	25% to 0%	25% to 5%
1	-34,001	-26,078	7,288
2	19,585	-19,196	-40,830
3	-2,553	4,175	6,684
4	-20,624	-3,997	15,793
5	60,735	8,872	-61,421
6	-3,644	-4,219	-570
7	-51,928	67,007	104,968
8	-13,552	23,950	36,243
9	15,634	66,804	53,305
10	-49,092	-30,859	16,195
Average	-7,944	8,646	13,766
StdDev	34,282	34,816	46,342

Table E.12 Suffering reduction with regard to information deviation concerning model III, NT16R3Na9 problem

Dataset	Suffering reduction_NT16R3Na9_Model III		
	5% to 0%	25% to 0%	25% to 5%
1	66,406	3,467	-75,846
2	1,435	-6,678	-8,143
3	-77,166	19,577	80,771
4	-91,936	21,273	91,624
5	-28,375	111,555	130,445
6	-28,165	-17,653	9,805
7	503	24,545	24,073
8	12,922	-2,399	-15,846
9	-2,704	-17,726	-14,918
10	10,352	-43,908	-55,738
Average	-13,673	9,205	16,623
StdDev	45,740	41,702	66,036

Table E.13 Suffering reduction with regard to information deviation concerning model III, NT11R17Na47 problem

Dataset	Suffering reduction_NT11R17Na47_Model III		
	5% to 0%	25% to 0%	25% to 5%
1	-14,441	-22,247	-7,527
2	46,667	-124,355	-194,250
3	11,667	-53,209	-66,876
4	-5,797	-31,585	-25,410
5	109,796	143,392	46,749
6	61,156	39,422	-25,773
7	-44,196	88,865	119,524
8	102,884	56,635	-62,807
9	-29,559	-67,169	-34,963
10	-22,832	-4,258	17,547
Average	21,535	2,549	-23,379
StdDev	55,425	79,911	81,686

Table E.14 Suffering reduction with regard to information deviation concerning model III, NT16R17Na47 problem

Dataset	Suffering reduction_NT16R17Na47_Model III		
	5% to 0%	25% to 0%	25% to 5%
1	3,134	44,525	41,726
2	-103,122	-26,199	60,844
3	22,444	-54,535	-81,676
4	-93,664	92,689	150,284
5	150,390	50,796	-162,039
6	-17,846	33,380	48,986
7	43,823	-138,451	-205,332
8	58,732	100,569	49,249
9	-53,853	-5,466	42,519
10	-25,501	-68,026	-39,917
Average	-1,546	2,928	-9,536
StdDev	75,831	75,853	110,772

E.2.2 Effect of Information Deviation with Respect to Model IV

For R3Na9 problems, most of the effects (see Table E.15) are of small sizes. The indication on effect magnitude is confirmed by the suffering reduction figures that fluctuate around zero (see Tables E.16 and E.17). The exception is the effect size of NT16R3Na9_25% over NT16R3Na9_0%, -0.44, a medium magnitude. The average of the suffering reduction for this comparison is around one third of the total number of victims. Even though the related average value of suffering reduction is smaller than the standard deviation, the gap is not large. Among the 10 values of suffering reduction, 7 of them have values less than zero.

Table E.15 Effect size of information deviation with regard to model IV

No.	Problem	Deviation	Effect size	
			5%	25%
1.	NT11R3Na9	0%	0.07	0.15
		5%		0.09
2.	NT16R3Na9	0%	-0.16	-0.44
		5%		-0.27
3.	NT11R7Na47	0%	-0.46	-0.35
		5%		0.05
4.	NT16R7Na47	0%	0.12	0.47
		5%		0.29

Table E.16 Suffering reduction with regard to information deviation concerning model IV, NT11R3Na9 problem

Dataset	Suffering reduction_NT11R3Na9_Model IV		
	5% to 0%	25% to 0%	25% to 5%
1	9,657	79,665	71,785
2	111,625	140,334	40,211
3	-25,132	38,214	59,513
4	579	49,667	49,161
5	97,349	40,708	-75,466
6	-36,848	39,546	69,803
7	-109,003	-57,314	40,404
8	-9,596	-13,314	-3,629
9	52,672	-126,455	-207,077
10	-148,081	17,092	119,738
Average	-5,678	20,814	16,444
StdDev	81,904	73,486	93,960

Table E.17 Suffering reduction with regard to information deviation concerning model IV, NT16R3Na9 problem

Dataset	Suffering reduction_NT16R3Na9_Model IV		
	5% to 0%	25% to 0%	25% to 5%
1	-300,281	-608,993	-174,467
2	98,381	84,514	-18,540
3	131,124	65,979	-98,110
4	103,195	44,335	-80,020
5	-112,452	-79,961	25,223
6	-15,346	-28,209	-12,377
7	-200,729	-350,732	-99,054
8	4,758	-70,690	-76,379
9	-101,549	-46,599	43,603
10	63,308	-153,087	-258,298
Average	-32,959	-114,344	-74,842
StdDev	143,117	214,578	91,804

For R17Na47 problems, the insights look slightly different to the R3Na9 problems. The NT11R17Na47 problems, on one hand, show that both the effect sizes (see Table E.15) and averages of suffering reduction (Table E.18) suggest that model IV with 100% accurate information performs the best. The relatively large average values of suffering reduction indicate that inaccurate information on resource availability does have a rather serious effect on the model performance in minimising the unmet demands. With regard to 5% deviation and 0% deviation, 9 out of 10 of the suffering reduction values are negative. The NT16R17Na47 problems, on the other hand, suggest the opposite. Apart from the presence of 0.47 and 0.29 effect sizes regarding 0% and 5% deviations in comparison with 25% deviation (see Table E.15), the pattern of suffering reduction and the small values of the averages of the reductions suggest that the information deviation under concern does not affect model IV performance.

Table E.18 Suffering reduction with regard to information deviation concerning model IV, NT11R17Na47 problem

Dataset	Suffering reduction_NT11R17Na47_Model IV		
	5% to 0%	25% to 0%	25% to 5%
1	-70,430	-108,958	-32,638
2	-77,842	166,806	203,964
3	31,255	58,453	29,566
4	-236,440	-448,650	-132,146
5	-234,250	-542,111	-192,382
6	-97,031	-201,468	-83,641
7	-91,671	205,707	240,811
8	-55,217	-66,825	-10,169
9	-17,467	45,838	60,593
10	-165,591	-121,433	31,003
Average	-101,468	-101,264	11,496
StdDev	87,183	244,939	135,980

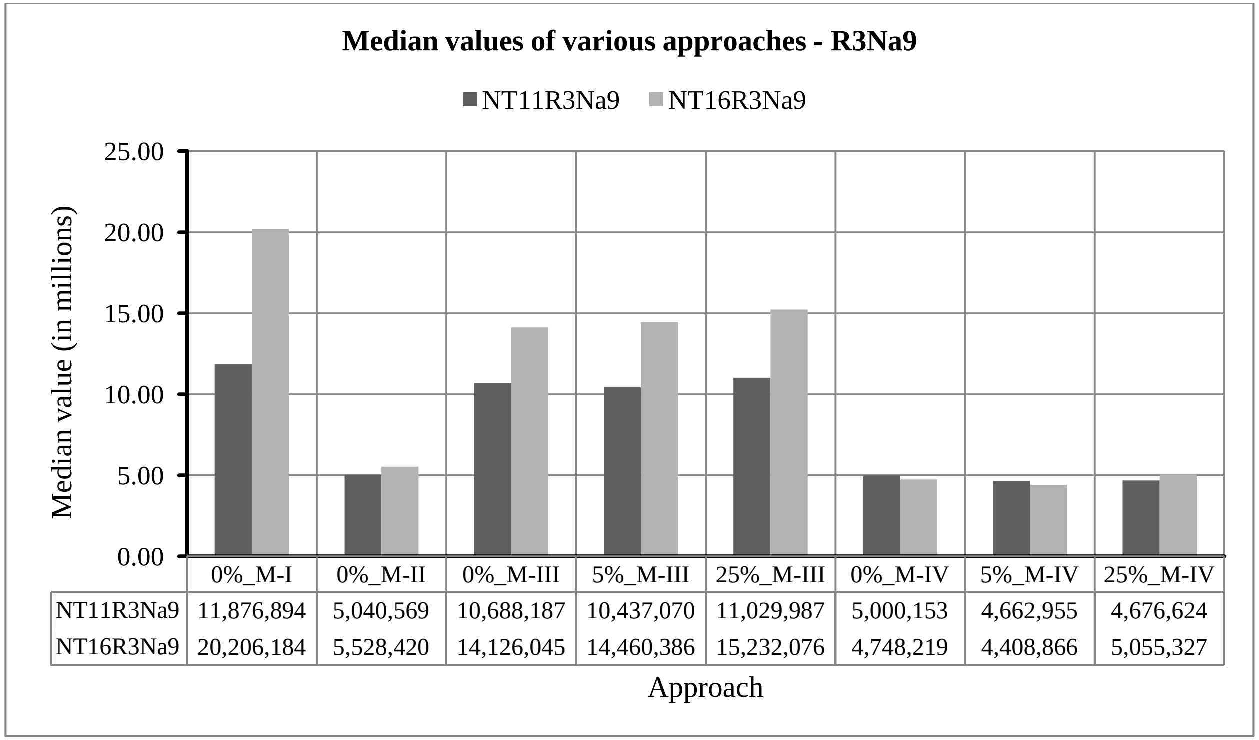
Table E.19 Suffering reduction with regard to information deviation concerning model IV, NT16R17Na47 problem

Dataset	Suffering reduction_NT16R17Na47_Model IV		
	5% to 0%	25% to 0%	25% to 5%
1	-113,324	6,723	93,032
2	211,124	194,977	-35,178
3	64,203	-118,146	-218,257
4	-96,859	89,190	149,054
5	66,368	96,644	36,480
6	141,246	211,384	109,923
7	-71,713	105,293	149,528
8	44,800	-34,782	-89,903
9	64,800	-58,412	-147,745
10	-306,741	-131,366	98,193
Average	390	36,150	14,513
StdDev	149,336	121,972	130,369

From the discussion and analyses with reference to the effect of information deviation on model III and model IV, it is not always the case that the models with more accurate information on resource availability perform better than the same models with less accurate information. Hence, it might be valuable to reexamine the performance of the four models when information on resource availability deviates from its real value. With this motivation, the median values of approaches relevant to a particular problem are provided in Figure E.14 and Figure E.15 (recall that information deviation applies only to models III and IV).

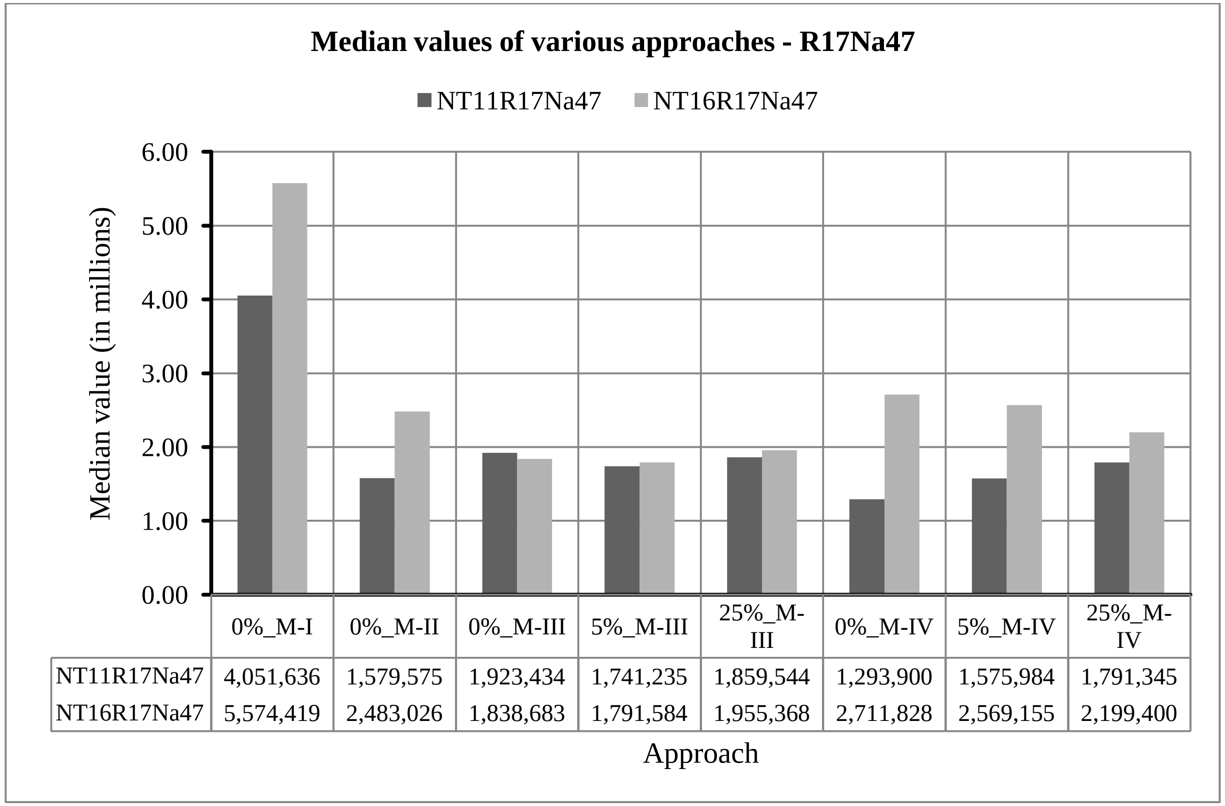
From Figure E.14, it is obvious that the fluctuation of median values with respect to model III and model IV as a result of the information deviation on resource availability does not change the position of the model performance relative to the other models. With respect to problems NT11R3Na9, for instance, it seems unambiguous that all three median values resulting from the application of model III (i.e. those with possible maximum information deviation 0%, 5% and 25%) are close to that resulting from the application of model I to the same problem. Even though there is variation, none of the three values relating to model III goes above the median value relating to model I. The insight that the fluctuating values of medians with regard to model III or model IV does not change the model performance's position relative to the others applies to all the R3Na9 problems.

With regard to the R17Na47 problems, Figure E.15 tells a slightly different story from that of Figure E.14. As in the R3Na9 problems, the median values in reference to model III and model IV also fluctuate over the three possible maximum deviations of information. What is interesting is that the medians with regard to model IV in a given problem fluctuate around the median value with respect to model II in the same problem. This suggests the likelihood that whatever the information deviation is, model IV and model II perform roughly equally for each of the R17Na47 problems. To put it another way, it is likely that maximum deviations of information considered in this thesis do not affect model IV performance relative to the performance of model II for the R17Na47 problems.



	0%_M-I	0%_M-II	0%_M-III	5%_M-III	25%_M-III	0%_M-IV	5%_M-IV	25%_M-IV
NT11R3Na9	11,876,894	5,040,569	10,688,187	10,437,070	11,029,987	5,000,153	4,662,955	4,676,624
NT16R3Na9	20,206,184	5,528,420	14,126,045	14,460,386	15,232,076	4,748,219	4,408,866	5,055,327

Figure E.14 Median values of various approaches in R3Na9 problems



	0%_M-I	0%_M-II	0%_M-III	5%_M-III	25%_M-III	0%_M-IV	5%_M-IV	25%_M-IV
NT11R17Na47	4,051,636	1,579,575	1,923,434	1,741,235	1,859,544	1,293,900	1,575,984	1,791,345
NT16R17Na47	5,574,419	2,483,026	1,838,683	1,791,584	1,955,368	2,711,828	2,569,155	2,199,400

Figure E.15 Median values of various approaches in R17Na47 problems

Appendix F Computational Results of Various Problem Sizes with Regard to Models – Heuristics-related Data

Table F.1 Maximum objective value for redtime

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	9,110,377.484934	2,412,929.054659	1,841,872.767773	2,113,481.809670
2	3,137,938.206562	1,576,900.598279	897,527.211415	1,712,816.602937
3	3,810,492.205599	1,196,472.808108	2,201,053.725137	2,145,087.285736
4	3,184,659.870254	1,090,444.829048	2,599,405.318331	1,111,404.874006
5	2,719,267.744584	2,682,665.189413	2,259,024.543225	1,733,103.228024
6	2,915,033.504404	1,983,556.696780	1,201,772.496321	918,643.552237
7	3,022,403.743986	1,106,160.292901	1,616,407.688234	1,058,054.473363
8	12,283,649.148136	2,796,847.533877	1,913,060.711295	2,762,813.347849
9	7,321,370.485474	2,199,449.626686	1,006,348.548579	1,885,608.857854
10	7,099,664.229056	2,641,912.382270	2,234,887.085293	2,352,422.767250
Average	5,460,485.662299	1,968,733.901202	1,777,136.009560	1,779,343.679893
StdDev	3,320,993.875638	680,256.781017	581,659.860301	602,412.769173

Table F.2 Maximum objective value for redtime_up

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	21,507,841.314477	2,907,461.450344	3,150,107.587679	1,944,661.206301
2	6,524,736.895127	1,328,756.884277	920,561.197313	1,175,510.708435
3	3,575,922.266625	2,003,195.023770	1,973,325.913181	1,122,033.799242
4	3,653,057.377608	1,009,581.897656	1,564,246.268931	1,308,509.908973
5	4,744,117.914957	1,472,061.748274	1,774,142.797639	1,658,400.129726
6	5,687,951.151076	1,542,426.778922	1,517,497.159536	1,640,113.548699
7	5,095,392.159699	1,634,008.825573	1,542,287.883353	1,068,930.057640
8	28,736,974.137465	1,592,680.086969	2,091,138.685984	1,807,846.002608
9	13,577,357.815814	1,543,421.147374	952,412.723784	1,640,228.212306
10	15,830,203.487918	1,333,670.890265	2,326,085.453540	1,756,241.785461
Average	10,893,355.452077	1,636,726.473342	1,781,180.567094	1,512,247.535939
StdDev	8,731,906.260132	513,779.579946	658,711.444487	314,762.774789

Table F.3 Maximum objective value for 4time

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	21,955,833.108536	2,539,782.206369	2,515,239.688947	1,906,337.699647
2	6,784,008.718064	1,449,370.286285	1,091,790.029297	1,480,694.180485
3	3,438,435.772361	1,816,848.858788	2,419,836.532804	2,089,580.437413
4	4,159,700.576237	930,078.251493	2,358,721.110878	1,158,214.795408
5	4,842,479.638134	1,516,670.122630	1,530,304.476321	1,288,592.372945
6	6,256,487.842317	1,539,258.173173	2,197,715.531151	1,995,786.558592
7	5,889,003.181436	1,241,957.182176	1,675,851.734599	1,550,434.015884
8	29,245,355.455758	2,952,522.666404	2,295,360.645013	3,079,291.881278
9	13,158,557.037926	1,020,131.575471	1,080,911.882342	885,321.432380
10	16,287,140.683501	1,106,469.998692	1,740,571.439593	1,006,726.243093
Average	11,201,700.201427	1,611,308.932148	1,890,630.307095	1,644,097.961713
StdDev	8,777,556.326163	662,351.406879	541,570.248971	652,398.626166

Table F.4 Maximum objective value for redNdc

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	15,940,298.888439	2,185,119.324047	3,909,736.713172	3,474,745.500391
2	4,968,099.604964	1,352,791.520798	2,984,643.266058	1,050,533.791688
3	3,205,787.471009	1,405,785.187246	2,270,839.987152	852,030.178982
4	2,935,706.189094	818,973.914956	1,810,559.150984	960,743.589883
5	4,623,659.767271	896,714.799912	2,104,720.297659	1,160,031.680170
6	5,935,894.485852	1,498,106.830047	4,161,784.786566	1,091,380.416472
7	5,212,942.865448	2,184,234.294521	2,199,091.186743	1,461,347.413700
8	31,866,915.512386	2,647,531.618069	8,159,022.653893	3,284,024.663780
9	12,575,514.930374	2,035,254.363751	6,397,028.747253	2,875,533.199808
10	15,082,770.251549	2,145,810.835681	5,663,779.246511	1,796,820.721222
Average	10,234,758.996639	1,717,032.268903	3,966,120.603599	1,800,719.115610
StdDev	9,037,510.437003	609,665.900941	2,146,940.299778	1,019,529.452131

Table F.5 Maximum objective value for redNdc6

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	15,940,298.888439	3,391,212.452467	1,891,379.974623	1,565,418.908656
2	4,968,099.604964	1,625,672.837809	1,023,369.438955	1,268,511.398818
3	3,205,787.471009	2,197,068.352809	1,811,693.599371	1,334,266.383224
4	2,935,706.189094	984,887.943753	1,805,693.552199	1,094,358.585412
5	4,623,659.767271	1,552,733.659419	2,036,602.899873	1,862,194.178934
6	5,935,894.485852	905,892.150700	2,601,556.547739	1,414,959.599577
7	5,212,942.865448	849,810.630799	1,684,824.311992	2,453,113.504206
8	31,866,915.512386	2,069,181.331440	3,338,676.669935	1,353,044.676698
9	12,575,514.930374	1,543,856.831577	1,514,701.196213	2,221,822.742238
10	15,082,770.251549	942,094.033624	2,185,103.084709	1,963,848.818524
Average	10,234,758.996639	1,606,241.022440	1,989,360.127561	1,653,153.879629
StdDev	9,037,510.437003	792,078.309914	629,114.621624	449,683.789661

Table F.6 Maximum objective value for redcomb

Dataset	Maximum Objective Value			
	M_I	M_II	M_III	M_IV
1	21,955,833.108536	1,862,006.650950	2,451,579.625750	1,406,296.448604
2	6,784,008.718064	855,988.775460	1,365,762.686472	838,982.219597
3	3,438,435.772361	1,224,167.271200	2,601,812.102088	1,230,004.630692
4	4,159,700.576237	788,653.194940	2,306,008.034922	1,261,461.614685
5	4,842,479.638134	1,348,525.180514	1,569,051.777618	1,079,394.577527
6	6,256,487.842317	1,273,171.300940	2,366,360.158599	1,511,520.660489
7	5,889,003.181436	1,123,684.549500	1,684,474.278752	822,728.015846
8	29,245,355.455758	1,917,541.634026	2,634,161.675226	1,134,870.375450
9	13,158,557.037926	1,314,806.848570	1,411,401.036999	1,130,428.126683
10	16,287,140.683501	1,645,988.752765	2,207,200.187413	1,125,362.334178
Average	11,201,700.201427	1,335,453.415887	2,059,781.156384	1,154,104.900375
StdDev	8,777,556.326163	380,511.482369	498,586.478571	217,328.247205

Appendix G Summary of Tests on Assumption with Respect to Residuals – Heuristics-related Data

Table G.1 Summary of tests on heuristics-related data with regard to models

No.	Data	*P* value, distribution	*P* value, equality of variance	*P* value, mean=0 or not
1.	redtime	<0.005, not normal	-	-
2.	redtime_up	<0.005, not normal	-	-
3.	4time	<0.005, not normal	-	-
4.	redNdc	<0.005, not normal	-	-
5.	redNdc6	<0.005, not normal	-	-
6.	redcomb	<0.005, not normal	-	-

Table G.2 Summary of tests on model-related data with regard to various approaches

No.	Data	*P* value, distribution	*P* value, equality of variance	*P* value, mean=0 or not
1.	Var_appr_model I	<0.005, not normal	-	-
2.	Var_appr_model II	0.042, not normal	-	-
3.	Var_appr_model III	<0.005, not normal	-	-
4.	Var_appr_model IV	0.034, not normal	-	-

Table G.3 Summary of tests on data related to models III and IV with regard to various approaches

No.	Data	*P* value, distribution	*P* value, equality of variance	*P* value, mean=0 or not
1.	model III	<0.005, not normal	-	-
2.	model IV	<0.005, not normal	-	-

Appendix H Suffering Reduction – Heuristics-related Data

Table H.1 Suffering reduction: redtime

Dataset	Suffering reduction, redtime					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
1	286,888	311,350	299,715	-120,993	-57,547	48,430
2	194,137	278,627	177,234	-295,393	-354,490	-33,636
3	267,712	164,829	170,560	178,112	9,923	-309,404
4	256,624	71,717	254,056	226,539	223,393	-7,501
5	5,253	66,050	141,526	-73,184	90,853	138,133
6	124,700	229,361	267,265	-253,866	91,939	209,512
7	247,422	181,540	253,633	123,188	134,802	16,971
8	301,392	329,470	302,473	-180,284	-173,342	4,749
9	273,011	336,606	289,739	-462,667	-340,964	55,685
10	245,029	267,402	260,941	-71,073	-20,524	42,762
Average	220,217	223,695	241,714	-92,962	-39,596	16,570
StdDev	91,148	99,873	57,675	219,877	195,762	135,292

Table H.2 Suffering reduction: redtime_up

Dataset	Suffering reduction, redtime_up					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
1	337,493	333,090	354,962	30,060	149,335	129,230
2	310,774	335,188	319,939	-173,044	-108,079	45,007
3	171,635	174,894	267,797	-5,907	168,352	171,661
4	282,396	223,142	250,462	138,377	63,801	-115,549
5	269,156	244,308	253,828	66,447	25,459	-49,399
6	284,422	286,132	277,720	-6,411	-31,533	-24,716
7	265,101	272,126	308,380	-23,208	119,774	134,957
8	368,618	361,849	365,697	93,022	52,868	-52,721
9	345,885	362,872	343,103	-242,163	-281,829	-24,477
10	357,369	332,904	346,952	166,497	95,603	-123,649
Average	299,285	292,651	308,884	4,367	25,375	9,034
StdDev	58,520	63,494	43,712	129,036	136,344	105,757

Table H.3 Suffering reduction: 4time

Dataset	Suffering reduction, 4time					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
1	345,104	345,541	356,363	-3,808	94,473	97,331
2	306,873	327,442	305,071	-127,813	-139,009	-8,434
3	184,043	115,606	153,089	97,244	53,260	-58,581
4	302,991	168,961	281,588	236,367	198,622	-95,723
5	268,021	266,922	286,402	3,477	61,640	58,686
6	294,236	253,165	265,760	116,922	35,856	-115,743
7	307,946	279,193	287,504	101,039	29,205	-96,929
8	350,849	359,618	349,157	-111,728	-133,280	-16,756
9	359,993	358,190	363,991	21,944	70,615	51,571
10	363,735	348,542	366,125	142,170	164,533	35,179
Average	308,379	282,318	301,505	47,581	43,591	-14,940
StdDev	53,955	84,255	64,549	113,581	109,185	74,774

Table H.4 Suffering reduction: redNdc

Dataset	Suffering reduction, redNdc					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
1	336,751	294,530	305,179	172,141	43,418	-230,318
2	283,984	155,802	307,727	213,367	252,888	87,194
3	219,118	113,813	286,528	148,661	243,824	153,723
4	281,380	149,567	262,534	213,726	183,169	-67,554
5	314,562	212,604	292,338	223,983	175,160	-114,595
6	291,756	116,636	318,496	249,771	287,909	105,950
7	226,733	225,620	280,849	2,636	130,919	129,155
8	357,825	290,330	350,030	263,615	233,172	-93,819
9	327,088	191,733	301,013	266,087	214,827	-161,118
10	334,727	243,704	343,757	242,396	266,442	63,469
Average	297,392	199,434	304,845	199,638	203,173	-12,791
StdDev	46,379	65,626	27,128	78,877	73,235	136,233

Table H.5 Suffering reduction: redNdc6

Dataset	Suffering reduction, redNdc6					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
1	307,224	343,943	351,923	-309,459	67,255	210,105
2	262,549	309,861	290,605	-229,680	-93,481	85,738
3	122,793	169,706	227,824	-83,011	102,840	153,252
4	259,325	150,214	244,773	177,393	153,734	-43,376
5	259,193	218,353	233,074	92,717	33,420	-77,776
6	330,690	219,211	297,222	254,358	177,996	-219,300
7	326,629	264,119	206,604	193,410	-177,955	-736,263
8	364,907	349,361	373,677	148,387	232,094	135,063
9	342,338	343,242	321,299	-7,512	-182,183	-171,372
10	365,872	333,710	339,435	221,994	39,515	-423,245
Average	294,152	270,172	288,644	45,860	35,323	-108,717
StdDev	72,900	76,352	58,119	196,611	144,561	294,701

Table H.6 Suffering reduction: redcomb

Dataset	Suffering reduction, redcomb					
	II to I	III to I	IV to I	II to III	IV to III	IV to II
1	357,151	346,672	365,251	93,849	166,390	95,510
2	341,007	311,682	341,985	145,661	150,520	7,753
3	251,310	94,953	250,647	206,634	205,758	-1,861
4	316,259	173,906	271,902	256,783	176,769	-233,958
5	281,572	263,800	303,260	54,848	121,785	77,883
6	310,833	242,646	295,966	180,283	140,975	-73,058
7	315,784	278,622	335,727	129,920	199,643	104,520
8	364,660	355,097	375,103	106,166	222,118	159,285
9	351,253	348,389	356,722	26,708	77,688	54,725
10	350,808	337,362	363,283	99,226	191,276	123,435
Average	324,064	275,313	325,985	130,008	165,292	31,423
StdDev	36,344	85,631	43,024	69,809	43,756	115,460

Appendix I Suffering Reduction of Model across Various Approaches

Table I.1.1 Suffering reduction of model I: heuristics vs. direct solution

Dataset	Suffering reduction with respect to direct solution					
	redtime	redtime_up	4time	redNdc	redNdc6	redcomb
1	167,209	-136,303	-147,271	0	0	-147,271
2	143,760	-122,275	-142,641	0	0	-142,641
3	-73,612	-45,057	-28,321	0	0	-28,321
4	-33,094	-95,358	-162,707	0	0	-162,707
5	160,735	-10,167	-18,469	0	0	-18,469
6	198,602	16,301	-21,077	0	0	-21,077
7	163,986	8,800	-50,611	0	0	-50,611
8	239,820	38,330	32,104	0	0	32,104
9	163,048	-31,089	-18,093	0	0	-18,093
10	206,552	-19,339	-31,162	0	0	-31,162
Average	133,701	-39,616	-58,825	0	0	-58,825
StdDev	102,909	59,829	66,985	0	0	66,985

Table I.1.2 Suffering reduction of model I: other heuristics vs. redtime

Dataset	Suffering reduction with respect to redtime				
	redtime_up	4time	redNdc	redNdc6	redcomb
1	-531,051	-550,241	-292,563	-292,563	-550,241
2	-421,196	-453,440	-227,606	-227,606	-453,440
3	24,023	38,104	61,930	61,930	38,104
4	-57,397	-119,481	30,507	30,507	-119,481
5	-290,590	-304,706	-273,303	-273,303	-304,706
6	-371,221	-447,334	-404,415	-404,415	-447,334
7	-267,660	-370,130	-282,838	-282,838	-370,130
8	-522,716	-538,867	-622,153	-622,153	-538,867
9	-333,459	-311,136	-280,059	-280,059	-311,136
10	-479,891	-505,008	-438,807	-438,807	-505,008
Average	-325,116	-356,224	-272,931	-272,931	-356,224
StdDev	187,054	190,704	203,730	203,730	190,704

Table I.1.3 Suffering reduction of model I: other heuristics vs. redtime_up

Dataset	Suffering reduction with respect to redtime_up			
	4time	redNdc	redNdc6	redcomb
1	-8,129	101,020	101,020	-8,129
2	-15,507	93,103	93,103	-15,507
3	15,004	40,393	40,393	15,004
4	-54,123	76,633	76,633	-54,123
5	-8,091	9,909	9,909	-8,091
6	-39,007	-17,011	-17,011	-39,007
7	-60,781	-9,003	-9,003	-60,781
8	-6,904	-42,504	-42,504	-6,904
9	12,037	28,795	28,795	12,037
10	-11,264	18,426	18,426	-11,264
Average	-17,677	29,976	29,976	-17,677
StdDev	25,684	48,115	48,115	25,684

Table I.1.4 Suffering reduction of model I: comparing different heuristics

Dataset	Suffering reduction with respect to 4time, reNdc and reNdc6					
	redNdc to 4time	redNdc6 to 4time	redcomb to 4time	redNdc6 to redNdc	redcomb to redNdc	redcomb to redNdc6
1	106,921	106,921	0	0	-147,271	-147,271
2	104,459	104,459	0	0	-142,641	-142,641
3	26,405	26,405	0	0	-28,321	-28,321
4	114,830	114,830	0	0	-162,707	-162,707
5	17,634	17,634	0	0	-18,469	-18,469
6	19,997	19,997	0	0	-21,077	-21,077
7	44,801	44,801	0	0	-50,611	-50,611
8	-34,982	-34,982	0	0	32,104	32,104
9	17,291	17,291	0	0	-18,093	-18,093
10	28,857	28,857	0	0	-31,162	-31,162
Average	44,621	44,621	0	0	-58,825	-58,825
StdDev	48,751	48,751	0	0	66,985	66,985

Table I.2.1 Suffering reduction of model II: heuristics vs. direct solution

Dataset	Suffering reduction with respect to direct solution					
	Redtime	redtime_up	4time	redNdc	redNdc6	redcomb
1	161,119	114,159	149,073	182,752	68,223	213,434
2	81,110	129,756	106,111	125,044	71,548	222,438
3	160,975	6,388	42,096	120,866	-30,762	155,668
4	105,074	126,221	147,013	176,069	132,679	183,998
5	-25,514	162,106	155,192	251,273	149,603	181,252
6	185,907	231,351	231,677	235,917	296,925	259,089
7	239,474	167,527	220,965	92,530	274,415	237,086
8	-9,005	162,891	-31,228	12,310	94,870	116,516
9	39,625	144,205	227,624	65,800	144,135	180,649
10	-91,416	147,097	188,520	-969	218,488	90,157
Average	84,735	139,170	143,704	126,159	142,012	184,029
StdDev	105,546	56,756	85,160	86,487	100,005	52,686

Table I.2.2 Suffering reduction of model II: other heuristics vs. redtime

Dataset	Suffering reduction with respect to redtime				
	redtime_up	4time	redNdc	redNdc6	redcomb
1	-79,982	-20,516	36,844	-158,219	89,102
2	61,410	31,561	55,462	-12,070	178,409
3	-263,124	-202,345	-68,270	-326,359	-9,033
4	28,939	57,392	97,154	37,777	108,005
5	176,106	169,617	259,802	164,371	194,077
6	86,788	87,412	95,508	212,021	139,762
7	-186,222	-47,908	-380,338	90,439	-6,182
8	168,019	-21,722	20,834	101,532	122,690
9	116,399	209,246	29,133	116,321	156,962
10	193,245	226,806	73,281	251,087	147,112
Average	30,158	48,954	21,941	47,690	112,090
StdDev	157,583	131,695	163,859	175,565	70,271

Table I.2.3 Suffering reduction of model II: other heuristics vs. redtime_up

Dataset	Suffering reduction with respect to redtime_up			
	4time	redNdc	redNdc6	redcomb
1	49,351	96,955	-64,930	140,324
2	-35,423	-7,059	-87,202	138,849
3	36,303	116,383	-37,769	151,764
4	30,732	73,678	9,545	85,398
5	-11,826	152,526	-21,386	32,750
6	802	11,213	161,049	68,124
7	93,633	-131,409	187,288	121,880
8	-333,196	-258,465	-116,755	-79,599
9	132,311	-124,358	-110	57,804
10	66,482	-237,641	114,580	-91,388
Average	2,917	-30,818	14,431	62,591
StdDev	128,115	148,446	105,138	87,379

Table I.2.4 Suffering reduction of model II: comparing different heuristics

Dataset	Suffering reduction with respect to 4time, redNdc and redNdc6					
	redNdc to 4time	redNdc6 to 4time	redcomb to 4time	redNdc6 to redNdc	redcomb to redNdc	redcomb to redNdc6
1	54,495	-130,825	104,143	-215,400	57,706	273,105
2	26,004	-47,470	159,770	-78,720	143,315	222,035
3	88,294	-81,669	127,304	-219,661	50,417	270,078
4	46,618	-22,997	59,340	-79,059	14,448	93,507
5	159,518	-9,279	43,265	-285,497	-196,626	88,871
6	10,433	160,577	67,461	154,268	58,594	-95,674
7	-296,082	123,220	37,164	238,415	189,483	-48,932
8	40,312	116,755	136,798	85,249	107,601	22,352
9	-388,331	-200,349	-112,727	94,222	138,141	43,919
10	-366,571	57,975	-190,286	218,913	90,900	-128,014
Average	-62,531	-3,406	43,223	-8,727	65,398	74,125
StdDev	203,997	117,680	111,978	192,224	105,816	144,871

Table I.3.1 Suffering reduction of model III: heuristics vs. direct solution

Dataset	Suffering reduction with respect to direct solution					
	redtime	redtime_up	4time	redNdc	redNdc6	redcomb
1	148,075	-23,934	59,539	-123,812	141,565	67,909
2	-16,007	-26,433	-103,937	-960,713	-72,968	-227,948
3	-62,204	-15,392	-107,177	-76,549	17,833	-144,584
4	-179,993	47,093	-127,193	-6,941	-5,874	-115,630
5	-63,540	33,861	82,843	-32,544	-18,861	75,060
6	194,019	142,466	31,399	-289,300	-34,542	3,862
7	-12,020	6,426	-26,813	-157,029	-29,046	-28,959
8	103,607	76,925	46,326	-832,244	-109,997	-4,437
9	-39,575	-16,539	-71,422	-2,341,992	-256,698	-212,577
10	-127,701	-148,837	-13,140	-922,366	-116,163	-121,284
Average	-5,534	7,564	-22,958	-574,349	-48,475	-70,859
StdDev	119,525	76,726	76,543	729,015	103,333	109,058

Table I.3.2 Suffering reduction of model III: other heuristics vs. redtime

Dataset	Suffering reduction with respect to redtime				
	redtime_up	4time	redNdc	redNdc6	redcomb
1	-277,182	-142,670	-438,129	-10,489	-129,182
2	-10,015	-84,466	-907,483	-54,717	-203,590
3	40,376	-38,790	-12,373	69,034	-71,054
4	155,408	36,134	118,429	119,159	44,048
5	83,763	125,887	26,656	38,423	119,193
6	-102,524	-323,409	-961,194	-454,547	-378,172
7	17,895	-14,351	-140,676	-16,518	-16,433
8	-36,326	-77,986	-1,274,119	-290,813	-147,098
9	20,916	-28,915	-2,090,426	-197,132	-157,073
10	-15,925	86,315	-598,739	8,693	4,835
Average	-12,362	-46,225	-627,805	-78,890	-93,453
StdDev	115,971	126,468	697,966	180,031	142,055

Table I.3.3 Suffering reduction of model III: other heuristics vs. redtime_up

Dataset	Suffering reduction with respect to redtime_up			
	4time	redNdc	redNdc6	redcomb
1	78,650	-94,106	155,936	86,536
2	-72,588	-875,012	-43,583	-188,731
3	-88,302	-58,837	31,965	-124,290
4	-198,205	-61,450	-60,236	-185,054
5	53,636	-72,715	-57,732	45,113
6	-174,928	-680,018	-278,782	-218,298
7	-33,796	-166,192	-36,066	-35,978
8	-38,112	-1,132,385	-232,815	-101,339
9	-52,652	-2,230,908	-230,395	-188,068
10	98,232	-559,964	23,653	19,945
Average	-42,807	-593,159	-72,806	-89,016
StdDev	99,279	693,742	136,649	110,846

Table I.3.4 Suffering reduction of model III: comparing different heuristics

Dataset	Suffering reduction with respect to 4time, redNdc and redNdc6					
	redNdc to 4time	redNdc6 to 4time	redcomb to 4time	redNdc6 to redNdc	redcomb to redNdc	redcomb to redNdc6
1	-216,360	96,794	9,877	201,461	145,545	-55,916
2	-676,577	24,456	-97,928	256,440	211,671	-44,768
3	24,029	98,075	-29,347	78,905	-56,878	-135,783
4	90,693	91,498	8,721	1,049	-106,789	-107,838
5	-146,483	-129,113	-9,881	12,630	99,321	86,691
6	-348,759	-71,710	-29,946	146,301	168,355	22,054
7	-121,844	-2,089	-2,008	91,261	91,323	62
8	-996,914	-177,380	-57,601	230,558	264,255	33,697
9	-1,919,304	-156,613	-119,318	297,844	304,145	6,302
10	-879,608	-99,667	-104,621	239,689	238,166	-1,523
Average	-519,113	-32,575	-43,205	155,614	135,911	-19,702
StdDev	617,144	108,058	48,827	105,214	133,963	67,077

Table I.4.1 Suffering reduction of model IV: heuristics vs. direct solution

Dataset	Suffering reduction with respect to direct solution					
	redtime	redtime_up	4time	redNdc	redNdc6	redcomb
1	144,940	164,535	168,983	-13,059	208,553	227,021
2	234,597	283,424	255,691	294,781	274,972	314,005
3	-56,322	156,660	-44,766	212,870	112,477	134,182
4	186,439	150,295	177,855	214,067	189,565	158,922
5	164,094	173,842	222,098	238,874	147,249	249,397
6	272,313	179,693	134,032	250,138	208,597	196,201
7	220,540	218,796	141,565	155,854	-3,221	258,285
8	49,270	167,129	10,211	-15,056	223,259	250,185
9	-18,365	34,809	198,397	-232,883	-91,223	145,283
10	-14,837	87,824	216,890	80,837	52,075	196,461
Average	118,267	161,700	148,096	118,642	132,230	212,994
StdDev	118,701	66,916	95,502	164,100	114,952	57,189

Table I.4.2 Suffering reduction of model IV: other heuristics vs. redtime

Dataset	Suffering reduction with respect to redtime				
	redtime_up	4time	redNdc	redNdc6	redcomb
1	31,172	38,248	-251,353	101,198	130,579
2	122,419	52,887	150,894	101,230	199,094
3	186,120	10,098	235,241	147,509	166,477
4	-69,209	-16,436	52,902	5,985	-52,689
5	16,821	100,092	129,040	-29,068	147,197
6	-306,486	-457,579	-73,380	-210,839	-251,859
7	-4,011	-181,607	-148,748	-514,546	86,797
8	134,889	-44,703	-73,621	199,130	229,947
9	50,784	207,020	-204,875	-69,583	156,293
10	98,901	223,240	92,170	64,461	203,559
Average	26,140	-6,874	-9,173	-20,452	101,539
StdDev	138,782	197,549	164,416	209,975	147,366

Table I.4.3 Suffering reduction of model IV: other heuristics vs. redtime_up

Dataset	Suffering reduction with respect to redtime_up			
	4time	redNdc	redNdc6	redcomb
1	7,691	-307,051	76,105	108,037
2	-101,315	41,490	-30,874	111,721
3	-336,516	93,908	-73,815	-37,553
4	44,824	103,717	63,868	14,032
5	87,021	117,274	-47,956	136,249
6	-84,628	130,565	53,573	30,597
7	-175,788	-143,264	-505,340	89,884
8	-274,458	-318,652	98,175	145,271
9	179,609	-293,907	-138,374	121,293
10	166,547	-9,017	-46,131	140,185
Average	-48,701	-58,494	-55,077	85,972
StdDev	177,269	188,765	175,560	62,268

Table I.4.4 Suffering reduction of model IV: comparing different heuristics

Dataset	Suffering reduction with respect to 4time, redNdc and redNdc6					
	redNdc to 4time	redNdc6 to 4time	redcomb to 4time	redNdc6 to redNdc	redcomb to redNdc	redcomb to redNdc6
1	-321,069	69,790	102,364	214,436	232,307	17,871
2	113,372	55,922	169,128	-80,973	78,586	159,559
3	231,123	141,061	160,533	-220,874	-173,120	47,754
4	66,536	21,516	-34,788	-54,273	-122,149	-67,876
5	38,934	-173,714	63,355	-236,215	27,127	263,342
6	176,843	113,572	94,691	-115,703	-150,230	-34,528
7	22,423	-227,206	183,165	-264,847	170,541	435,388
8	-25,946	218,772	246,422	229,462	255,388	25,926
9	-877,279	-589,126	-108,042	88,717	236,833	148,116
10	-306,272	-371,019	-45,988	-36,276	145,832	182,109
Average	-88,134	-74,043	83,084	-47,655	70,111	117,766
StdDev	332,247	258,375	114,540	177,241	166,949	152,700

Appendix J Detailed Analysis and Discussion on Heuristics-related Experiments

J.1 Model Performance within Proposed Heuristics

In this part, performance of the four location-allocation models in dealing with the relief distribution and victim evacuation for each of the proposed heuristics is compared and contrasted. The comparison is carried out by the aid of MW's *P* value, ES and average and standard deviation of SR with respect to relevant data. The Mann-Whitney (MW) test in particular is included as it is suggested by the Kruskal-Wallis test, summarised in Table J.1, that at least one of the models perform differently from the other three within the context of each of the proposed heuristics.

Table J.1 Kruskal-Wallis tests, heuristics-related data

No.	Heuristics approach	Model	Average rank	Median	P value
1.	redtime	I	35.3	3,497,576	0.000
		II	17.7	2,091,503	
		III	14.6	1,877,467	
		IV	14.4	1,809,356	
2.	redtime_up	I	35.5	6,106,344	0.000
		II	14.5	1,542,924	
		III	17.3	1,669,195	
		IV	14.7	1,640,171	
3.	4time	I	35.5	6,520,248	0.000
		II	13.7	1,483,020	
		III	18.5	1,969,143	
		IV	14.3	1,515,564	
4.	redNdc	I	32.9	5,574,419	0.000
		II	11.8	1,766,681	
		III	25.2	3,447,190	
		IV	12.1	1,310,690	
5.	redNdc6	I	35.1	5,574,419	0.000
		II	13.0	1,548,295	
		III	19.2	1,851,537	
		IV	14.7	1,490,189	
6.	redcomb	I	35.5	6,520,248	0.000
		II	13.1	1,293,989	
		III	24.1	2,256,604	
		IV	9.3	1,132,649	

J.1.1 Model Performance for redtime

With regard to the redtime heuristic, Table J.2 suggests that models II, III and IV perform better than model I does both statistically and practically. The same table, on the other hand, indicates that the performance of models II, III and IV for the redtime heuristic is not different from each other either statistically or practically. This means that the related heuristic does not make model II and model IV perform better than model III does, let alone model IV in contrast to model II.

Table J.2 Mann-Whitney's (MW's) *P* value, effect size (ES), and suffering reduction (SR) average and standard deviation, redtime

Relative to model …	Value of …	With respect to model …		
		III	II	IV
I	MW's P	0.0002	0.0002	0.0002
	ES	1.40	1.32	1.40
	SR Average	223,695	220,217	241,714
	SR StdDev	99,873	91,148	57,675
III	MW's P		0.4727	0.9698
	ES		-0.28	0.00
	SR Average		-92,962	-39,596
	SR StdDev		219,877	195,762
II	MW's P			0.4274
	ES			0.27
	SR Average			16,570
	SR StdDev			135,292

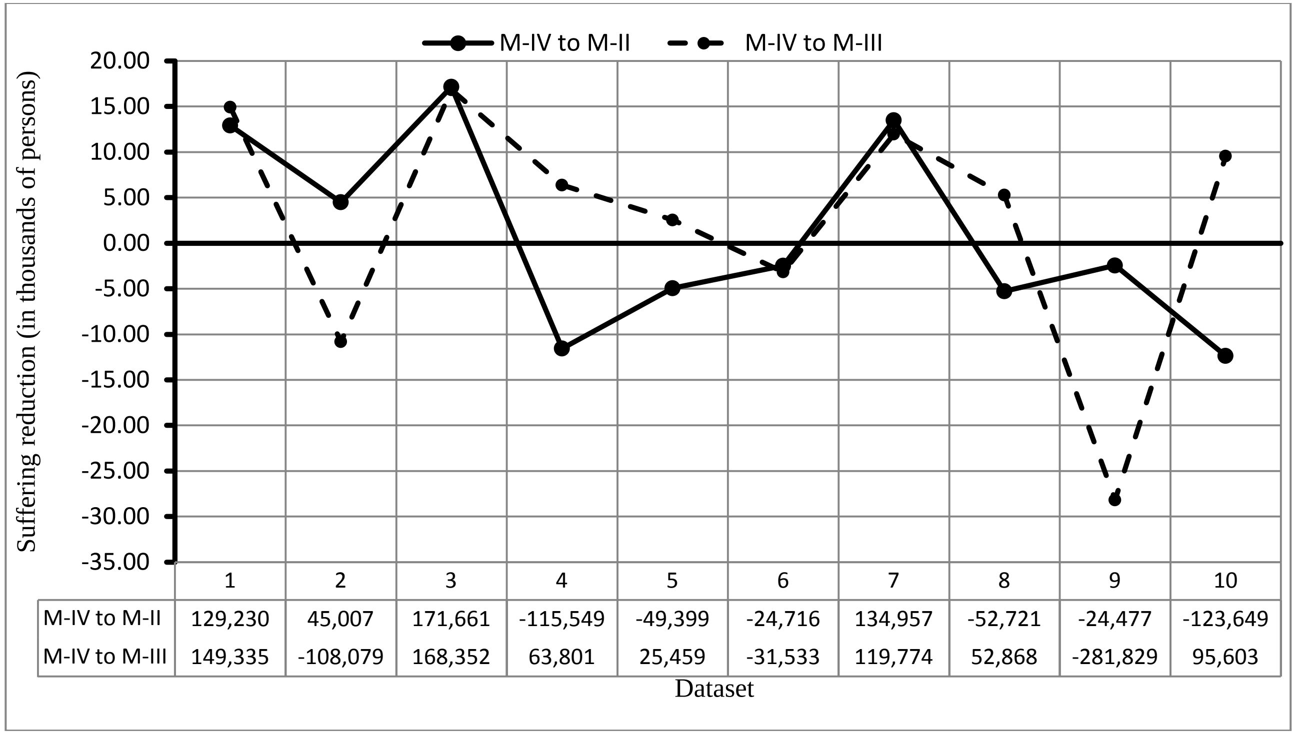
J.1.2 Model Performance for redtime_up

The MW's *P*, ES, and SR average and standard deviation for the redtime_up heuristic can be seen in Table J.3.

From Table J.3, there is strong statistical and practical evidence that the performance of models II, III and IV for redtime_up is better than that of model I. Model II performs relatively the same as model III does. The fact that the SR values related to models II and IV fluctuate around zero in a relatively balanced number (see Figure J.1), that the MW's *P* value of model IV over model II is relatively large and that the related ES is of small size suggest that the two carry out unmet demand minimisation for redtime_up at relatively the same level of performance. Contrasting model IV to model III, in the meantime, suggests that the former does the minimisation of unmet demand significantly better than the latter. This is supported by the medium size of related ES and the fact that, referring to Figure J.1, 7 out of 10 data sets of related SR lie above zero.

Table J.3 Mann-Whitney's (MW's) *P* value, effect size (ES), and suffering reduction (SR) average and standard deviation, redtime_up

Relative to model …	Value of …	With respect to model …		
		III	II	IV
I	MW's P	0.0002	0.0002	0.0002
	ES	1.34	1.36	1.38
	SR Average	292,651	299,285	308,884
	SR StdDev	63,494	58,520	43,712
III	MW's P		0.5708	0.4727
	ES		0.22	0.47
	SR Average		4,367	25,375
	SR StdDev		129,036	136,344
II	MW's P			0.9097
	ES			0.27
	SR Average			9,034
	SR StdDev			105,757



	1	2	3	4	5	6	7	8	9	10
M-IV to M-II	129,230	45,007	171,661	-115,549	-49,399	-24,716	134,957	-52,721	-24,477	-123,649
M-IV to M-III	149,335	-108,079	168,352	63,801	25,459	-31,533	119,774	52,868	-281,829	95,603

Figure J.1 Suffering reduction of model IV relative to model II and model III – redtime_up

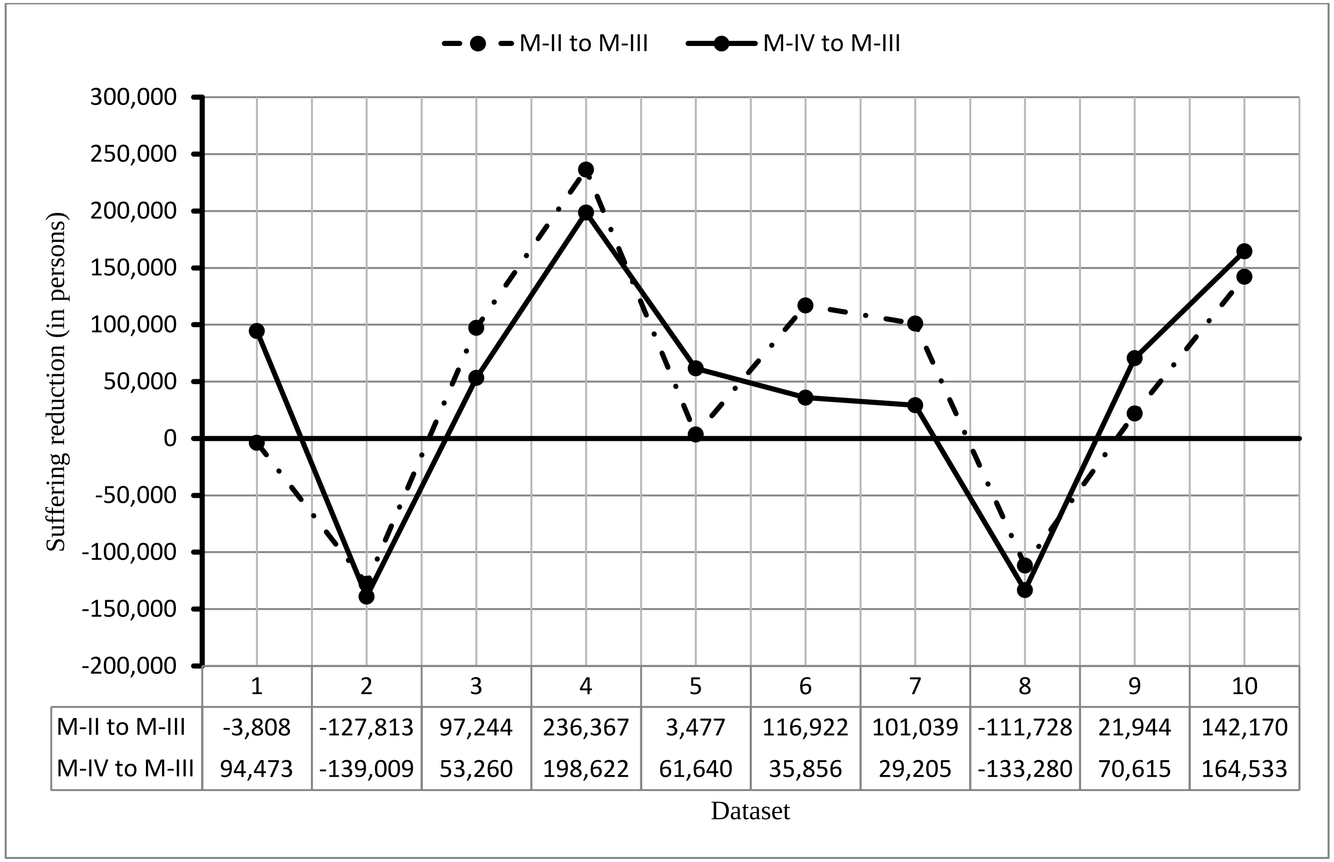
J.1.3 Model Performance for 4time

Inference about performance of model I, model II, model III and model IV for the 4time heuristic is derived from Table J.4 and Figure J.2.

Table J.4 Mann-Whitney's (MW's) *P* value, effect size (ES), and suffering reduction (SR) average and standard deviation, 4time

Relative to model …	Value of …	With respect to model …		
		III	II	IV
I	MW's P	0.0002	0.0002	0.0002
	ES	1.36	1.40	1.40
	SR Average	282,318	308,379	301,505
	SR StdDev	84,255	53,955	64,549
III	MW's P		0.3075	0.2413
	ES		0.42	0.37
	SR Average		47,581	43,591
	SR StdDev		113,581	109,185
II	MW's P			0.7913
	ES			-0.05
	SR Average			-14,940
	SR StdDev			74,774

From Table J.4 it is evident that, for the 4time heuristic, model I is outperformed by models II, III and IV. Model II and model IV, in the meantime, have relatively equal performances. In terms of models II, III and IV, the rather medium size of ES values proposes an idea that the performance of model II and model IV surpass that of model III. This proposal is confirmed by the plotted values of related SR (see Figure J.2), where 7 out of 10 datasets of model II-model III SR and 8 out of 10 datasets of model IV-model III SR lie above zero.



	1	2	3	4	5	6	7	8	9	10
M-II to M-III	-3,808	-127,813	97,244	236,367	3,477	116,922	101,039	-111,728	21,944	142,170
M-IV to M-III	94,473	-139,009	53,260	198,622	61,640	35,856	29,205	-133,280	70,615	164,533

Figure J.2 Suffering reduction of model IV and model II to model III - 4time

J.1.4 Model Performance for redNdc

The idea of reducing the distribution centres to establish from 17 to 1 only really affects the performance of model III. As can be seen from Table J.5, the ES values and the averages and standard deviations of SRs concerning model IV and model II in comparison with model III indicate that model III, for the redNdc heuristic, performs worse than models II and IV. Model II and model IV themselves, in the meantime, perform relatively equivalently. The table also suggests that the other three models have dominant performance over model I for the redNdc heuristic.

Table J.5 Mann-Whitney's (MW's) *P* value, effect size (ES), and suffering reduction (SR) average and standard deviation, redNdc

Relative to model …	Value of …	With respect to model …		
		III	II	IV
I	MW's P	0.0376	0.0002	0.0006
	ES	0.87	1.21	1.19
	SR Average	199,434	297,392	304,845
	SR StdDev	65,626	46,379	27,128
III	MW's P		0.0036	0.0073
	ES		1.29	1.17
	SR Average		199,638	203,173
	SR StdDev		78,877	73,235
II	MW's P			0.9097
	ES			-0.09
	SR Average			-12,791
	SR StdDev			136,233

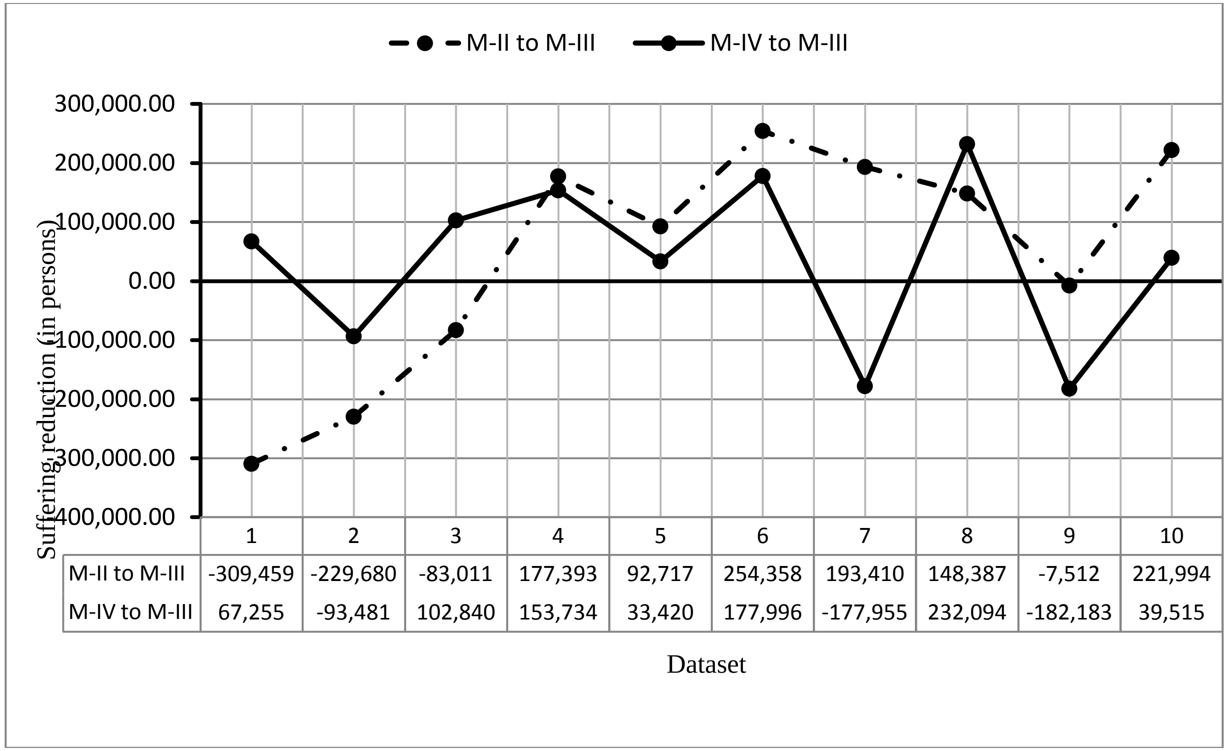
J.1.5 Model Performance for redNdc6

Similar to redNdc, the redNdc6 heuristic also merges the distribution centres into a smaller number. Instead of 1, however, redNdc6 proposes 6 as the new number of distribution centres to establish. For redNdc6, the performance pattern of the four models is slightly different from that for redNdc. As can be seen from Figure J.3, 4 out of 10 datasets of SR values with respect to model II over model III lie below zero. In spite of a medium effect size (i.e. 0.46), this fact along with the related SW's *P* value being higher than the critical *P* value indicate that model

II does not have dominant performance over model III. The indication that model IV, for redNdc6, performs better than model III, that model II and model IV have relatively the same performance and that the performance of model I is surpassed by the performance of the other three models is exactly the same as was witnessed for redNdc.

Table J.6 Mann-Whitney's (MW's) *P* value, effect size (ES), and suffering reduction (SR) average and standard deviation, redNdc6

Relative to model …	Value of …	With respect to model …		
		III	II	IV
I	MW's P	0.0003	0.0003	0.0002
	ES	1.17	1.22	1.22
	SR Average	270,172	294,152	288,644
	SR StdDev	76,352	72,900	58,119
III	MW's P		0.1620	0.2413
	ES		0.49	0.56
	SR Average		45,860	35,323
	SR StdDev		196,611	144,561
II	MW's P			0.5708
	ES			-0.07
	SR Average			-108,717
	SR StdDev			294,701



	1	2	3	4	5	6	7	8	9	10
M-II to M-III	-309,459	-229,680	-83,011	177,393	92,717	254,358	193,410	148,387	-7,512	221,994
M-IV to M-III	67,255	-93,481	102,840	153,734	33,420	177,996	-177,955	232,094	-182,183	39,515

Figure J.3 Suffering reduction of model II and model IV to model III – redNdc6

J.1.6 Model Performance for redcomb

From Table J.7, it is evident that models II, III and IV perform much better than model I does for the redcomb heuristic. It is also apparent that model II and model IV carry out the process of delivering relief and evacuating injured victims much better than model III does. The majority of SR values in terms of model IV over model II – 7 out of 10; see Figure J.4 - and the related ES of medium magnitude recommend that model IV, for redcomb, performs relatively better than model II.

Table J.7 Mann-Whitney's (MW's) *P* value, effect size (ES), and suffering reduction (SR) average and standard deviation, redcomb

Relative to model …	Value of …	With respect to model …		
		III	II	IV
I	MW's P	0.0002	0.0002	0.0002
	ES	1.34	1.44	1.47
	SR Average	275,313	324,064	325,985
	SR StdDev	85,631	36,344	43,024
III	MW's P		0.0036	0.0004
	ES		1.48	2.14
	SR Average		130,008	165,292
	SR StdDev		69,809	43,756
II	MW's P			0.2730
	ES			0.53
	SR Average			31,423
	SR StdDev			115,460

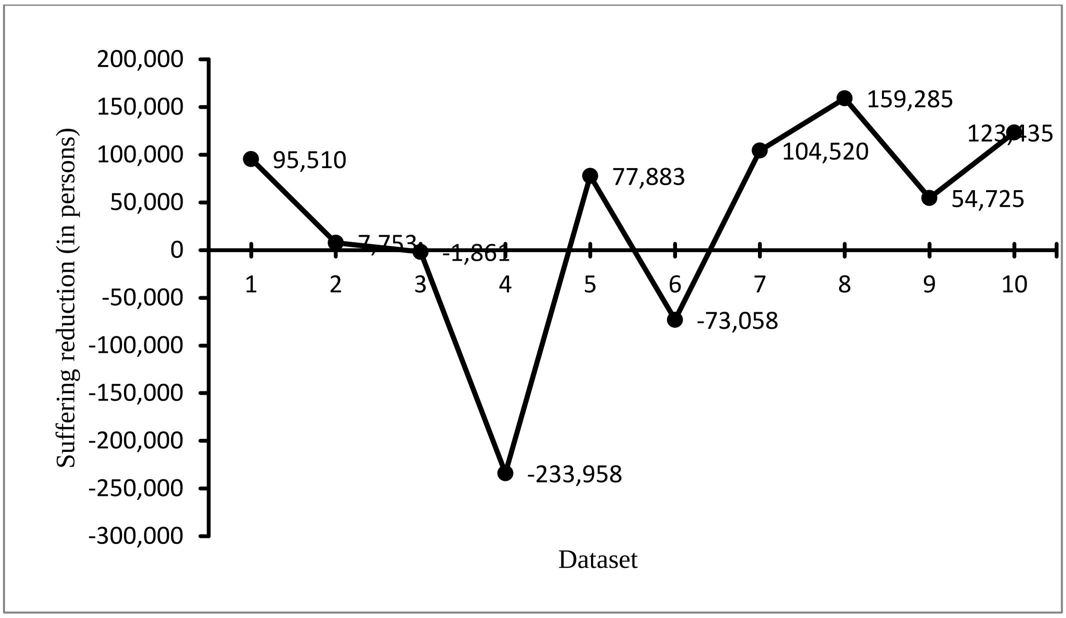


Figure J.4 Suffering reduction of model IV to model II – redcomb

J.2 Performance of the Heuristic Approaches for Each Model

Tables J.8 to J.11 show test results on the performance of different solution approaches for solving the four models respectively. These approaches include solving the models directly as described in Chapter 4 and the heuristic approaches proposed in Chapter 5 and this appendix. Time limits for all approaches are set the same. From Tables J.9 to J.11, it can be inferred that, statistically speaking, at least one heuristic performs differently compared to the others, for model II, model III and model IV. With regard to Table J.8, in the meantime, the *P* value (i.e. 0.409) which is greater than the critical *P* value (i.e. 0.05) suggests that there is no statistical evidence that one approach gives model I different performance in comparison to the other approaches. MW's *P* values of various approaches with respect to each of the four models are presented in Tables J.12–J.15 along with ES values and SR average and standard deviation. These indicators are presented in order to give a starting point for the discussion on the performance of the heuristics presented in this appendix for solving each of the four models.

Table J.8 Kruskal-Wallis test results of model I with regard to all approaches

Approach	Average rank	Median	P value
direct solution	35.5	5,574,419	0.409
redtime	21.8	3,497,576	
redtime_up	38.6	6,106,344	
4time	40.8	6,520,248	
redNdc	35.5	5,574,419	
redNdc6	35.5	5,574,419	
redcomb	40.8	6,520,248	

Table J.9 Kruskal-Wallis test result of model II with regard to all approaches

Approach	Average rank	Median	P value
direct solution	55.3	2,483,026	0.014
redtime	41.8	2,091,503	
redtime_up	33.3	1,542,924	
4time	30.4	1,483,020	
redNdc	34.9	1,766,681	
redNdc6	30.4	1,548,295	
redcomb	22.4	1,293,989	

Table J.10 Kruskal-Wallis test result of model III concerning all approaches

Approach	Average rank	Median	P value
direct solution	31.4	1,838,683	0.033
redtime	29.4	1,877,467	
redtime_up	27.0	1,669,195	
4time	32.8	1,969,143	
redNdc	56.0	3,447,190	
redNdc6	33.4	1,851,537	
redcomb	38.5	2,256,604	

Table J.11 Kruskal-Wallis test result of model IV regarding all approaches

Approach	Average rank	Median	P value
direct solution	59.0	2,711,828	0.001
redtime	38.1	1,809,356	
redtime_up	31.7	1,640,171	
4time	33.7	1,515,564	
redNdc	32.0	1,310,690	
redNdc6	36.8	1,490,189	
redcomb	17.2	1,132,649	

J.2.1 Performance of All Approaches for Model I

The Kruskal-Wallis test suggests that model I performs equally across the 0% problem approached using an exact method (in this sense, a mixed integer programming problem (MIP)) and the 0% problem approached using various heuristics. It is not surprising, therefore, that the MW's *P* values in Table J.12 give the same indication. Practically speaking, however, the ES values and the SR averages of model I with respect to redtime heuristic relative to other approaches (see Table J.12) and the fact that the majority of the related SR figures lie above zero (for SR values of redtime to direct solution; see Table I.1.1 of Appendix I) and below zero (for SR values of other approaches to redtime; see Table I.1.2 of Appendix I) provides sufficient evidence that redtime performance for model I is better than the other approaches (including direct solution). It is necessary to mention that the redNdc and redNdc6 approaches do not affect the total number of sub-regions as well as the total number of distribution centres needing to be established in model I. Consequently, model I performs exactly the same for direct solution, redNdc and redNdc6. With respect to redcomb, the inclusion of reducing the number of distribution centres to build and the idea of time point reduction as used in the 4time approach means model I performs exactly the same for redcomb and 4time. These all explain the presence of the 0.00 or 0 figures in Table J.12.

J.2.2 Performance of All Approaches for Model II

A numerical summary of the relative performance of all heuristics for model II can be seen in Table J.13 and Tables I.2.1-I.2.4 of Appendix I. Although the majority of MW's *P* values are larger than the critical *P* value (i.e. 0.0024) (see Table J.13), the large size of ES and relative large SR averages (see Table J.13) and the fact that the majority of the related SR figures lie above zero (see Table I.2.1 of Appendix I of the thesis) provide strong evidence that for Model II all of the heuristics perform better than solving the model directly. Despite insignificance from a statistical viewpoint (see the MW's values in Table J.13), ES values which are at least of medium size (see Table J.13) and SR figures which mostly lie above zero (see Table I.2.2 of Appendix I) suggest that redtime_up, redNdc, redNdc6 and redcomb improve model II performance in comparison with the performance of the same model resulting from the implementation of the redtime approach. Table J.13 (see the last column) and Tables I.2.1-I.2.4 also show that model II performance using redcomb is better than that resulting from the other approaches. It is very likely that the last observation is due to the fact that redcomb reduces the solution space of model II the most as compared to the other approaches.

J.2.3 Performance of All Approaches for Model III

The idea of reducing the total number of distribution centres to build from 17 to 1 negatively affects the performance of model III, as can be seen in Table J.14. The table shows that all approaches apart from redNdc lead to model III ending up with a level of performance similar to that of direct solution.

J.2.4 Performance of All Approaches for Model IV

With reference to Table J.15, there is strong evidence that for solving model IV, the performance of any of the heuristics is better than direct solution. Concerning the heuristics themselves, it is also evident from the same table that redcomb gives the best performance. Again, this is most likely due to its further reduction of solution space.

Table J.12 Values of MW’s *P*, ES, and SR average and standard deviation of the results of various approaches for model I

Relative to approach …	Value of …	With respect to approach …					
		Redtime	redtime_up	4time	redNdc	redNdc6	redcomb
direct solution	MW’s *P*	0.1212	0.7337	0.5708	1.0000	1.0000	0.5708
	ES	0.64	-0.07	-0.10	0.00	0.00	-0.10
	SR Average	133,701	-39,616	-58,825	0	0	-58,825
	SR StdDev	102,909	59,829	66,985	0	0	66,985
redtime	MW’s *P*		0.0757	0.0640	0.1212	0.1212	0.0640
	ES		-0.75	-0.79	-0.64	-0.64	-0.79
	SR Average		-325,116	-356,224	-272,931	-272,931	-356,224
	SR StdDev		187,054	190,704	203,730	203,730	190,704
redtime_up	MW’s *P*			0.7913	0.7337	0.7337	0.7913
	ES			-0.03	0.07	0.07	-0.03
	SR Average			-17,677	29,976	29,976	-17,677
	SR StdDev			25,684	48,115	48,115	25,684
4time	MW’s *P*				0.5708	0.5708	1.0000
	ES				0.10	0.10	0.00
	SR Average				44,621	44,621	0
	SR StdDev				48,751	48,751	0
redNdc	MW’s *P*					1.0000	0.5708
	ES					0.00	-0.10
	SR Average					0	-58,825
	SR StdDev					0	66,985
redNdc6	MW’s *P*						0.5708
	ES						-0.10
	SR Average						-58,825
	SR StdDev						66,985

Table J.13 Values of MW’s *P*, ES, and SR average and standard deviation of the results of various approaches for model II

Relative to approach …	Value of …	With respect to approach …					
		redtime	redtime_up	4time	redNdc	redNdc6	redcomb
direct solution	MW’s *P*	0.1212	0.0073	0.0140	0.0312	0.0173	0.0004
	ES	0.78	1.30	1.23	1.13	1.14	1.83
	SR Average	84,735	139,170	143,704	126,159	142,012	184,029
	SR StdDev	105,546	56,756	85,160	86,487	100,005	52,686
redtime	MW’s *P*		0.3847	0.2730	0.3447	0.1405	0.0757
	ES		0.50	0.48	0.35	0.45	1.04
	SR Average		30,158	48,954	21,941	47,690	112,090
	SR StdDev		157,583	131,695	163,859	175,565	70,271
redtime_up	MW’s *P*			0.5205	0.7337	0.8501	0.1620
	ES			0.04	-0.13	0.04	0.61
	SR Average			2,917	-30,818	14,431	62,591
	SR StdDev			128,115	148,446	105,138	87,379
4time	MW’s *P*				0.7913	0.9698	0.5205
	ES				-0.15	0.01	0.46
	SR Average				-62,531	-3,406	43,223
	SR StdDev				203,997	117,680	111,978
redNdc	MW’s *P*					0.8501	0.0757
	ES					0.14	0.68
	SR Average					-8,727	65,398
	SR StdDev					192,224	105,816
redNdc6	MW’s *P*						0.5708
	ES						0.40
	SR Average						74,125
	SR StdDev						144,871

Table J.14 Values of MW’s *P*, ES, and SR average and standard deviation of the results of various approaches for model III

Relative to approach …	Value of …	With respect to approach …					
		redtime	redtime_up	4time	redNdc	redNdc6	redcomb
direct solution	MW’s *P*	0.9097	0.7337	1.0000	0.0073	0.7337	0.6232
	ES	0.12	0.11	-0.04	-1.20	-0.18	-0.30
	SR Average	-5,534	7,564	-22,958	-574,349	-48,475	-70,859
	SR StdDev	119,525	76,726	76,543	729,015	103,333	109,058
redtime	MW’s *P*		0.7913	0.6232	0.0091	0.7913	0.2123
	ES		-0.01	-0.18	-1.26	-0.32	-0.47
	SR Average		-12,362	-46,225	-627,805	-78,890	-93,453
	SR StdDev		115,971	126,468	697,966	180,031	142,055
redtime_up	MW’s *P*			0.4727	0.0036	0.4274	0.2413
	ES			-0.16	-1.25	-0.29	-0.43
	SR Average			-42,807	-593,159	-72,806	-89,016
	SR StdDev			99,279	693,742	136,649	110,846
4time	MW’s *P*				0.0173	0.9698	0.4274
	ES				-1.20	-0.15	-0.30
	SR Average				-519,113	-32,575	-43,205
	SR StdDev				617,144	108,058	48,827
redNdc	MW’s *P*					0.0073	0.0452
	ES					1.14	1.11
	SR Average					155,614	135,911
	SR StdDev					105,214	133,963
redNdc6	MW’s *P*						0.6776
	ES						-0.11
	SR Average						-19,702
	SR StdDev						67,077

Table J.15 Values of MW’s *P*, ES, and SR average and standard deviation of the results of various approaches for model IV

Relative to approach …	Value of …	With respect to approach …					
		redtime	redtime_up	4time	redNdc	redNdc6	redcomb
direct solution	MW’s *P*	0.0113	0.0004	0.0058	0.0376	0.0036	0.0002
	ES	1.25	1.87	1.38	0.94	1.55	2.51
	SR Average	118,267	161,700	148,096	118,642	132,230	212,994
	SR StdDev	118,701	66,916	95,502	164,100	114,952	57,189
redtime	MW’s *P*		0.3075	0.5205	0.7337	0.7337	0.0452
	ES		0.50	0.20	-0.02	0.22	1.25
	SR Average		26,140	-6,874	-9,173	-20,452	101,539
	SR StdDev		138,782	197,549	164,416	209,975	147,366
redtime_up	MW’s *P*			0.9097	0.7337	0.5205	0.0312
	ES			-0.23	-0.35	-0.33	1.20
	SR Average			-48,701	-58,494	-55,077	85,972
	SR StdDev			177,269	188,765	175,560	62,268
4time	MW’s *P*				0.8501	0.7913	0.0452
	ES				-0.17	-0.01	0.92
	SR Average				-88,134	-74,043	83,084
	SR StdDev				332,247	258,375	114,540
redNdc	MW’s *P*					0.5708	0.3075
	ES					0.17	0.80
	SR Average					-47,655	70,111
	SR StdDev					177,241	166,949
redNdc6	MW’s *P*						0.0073
	ES						1.28
	SR Average						117,766
	SR StdDev						152,700

Appendix K Assumption Tests on Residuals – Best Approach for Each Model

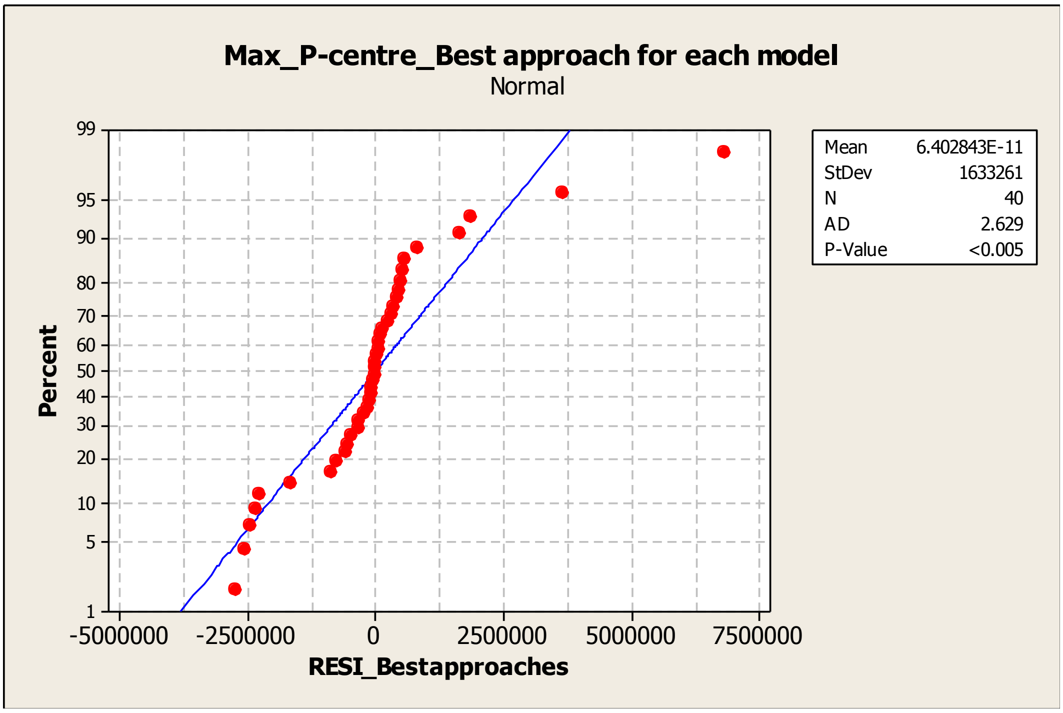


Figure K.1 Normality plot of residuals – best approach for each model

Appendix L Suffering Reduction with Regard to the Best Approach for Each Model

Table L.1 Suffering reduction of models with their best approach relative to model I_redtime

Dataset	M_III_redtime to M_I_redtime	M_II_redcomb to M_I_redtime	M_IV_redcomb to M_I_redtime
1	311,350	310,487	330,008
2	278,627	283,793	285,908
3	164,829	264,875	264,278
4	71,717	293,606	235,668
5	66,050	196,718	235,341
6	229,361	219,803	187,894
7	181,540	245,159	284,018
8	329,470	329,327	354,193
9	336,606	320,165	329,992
10	267,402	299,772	328,389
Average	223,695	276,370	283,569
StdDev	99,873	44,016	53,188

Table L.2 Suffering reduction of models with their best approach relative to models other than model I

Dataset	M_II_redcomb to M_III_redtime	M_IV_redcomb to M_III_redtime	M_IV_redcomb to M_II_redcomb
1	-4,266	92,288	95,510
2	18,061	25,456	7,753
3	173,202	172,167	-1,861
4	271,847	200,865	-233,958
5	157,289	203,781	77,883
6	-23,185	-100,583	-73,058
7	118,957	191,617	104,520
8	-914	158,744	159,285
9	-119,616	-48,116	54,725
10	102,831	193,741	123,435
Average	69,421	108,996	31,423
StdDev	115,645	112,429	115,460