A study of optimal facility location problem in disaster management and humanitarian logistics

その他（別言語等）のタイトル	人道援助ロジスティクスと災害マネジメントにおける最適施設位置決定問題に関する研究
著者	BOONMEE Chawis
学位名	博士（工学）
学位の種別	課程博士
報告番号	甲第426号
研究科・専攻	工学専攻・先端環境創生工学コース
学位授与年月日	2018-09-26
URL	http://doi.org/10.15118/00009701

Muroran IT

MURORAN INSTITUTE OF TECHNOLOGY

DISSERTATION A STUDY OF OPTIMAL FACILITY LOCATION PROBLEM IN DISASTER MANAGEMENT AND HUMANITARIAN LOGISTICS

Chawis Boonmee

A STUDY OF OPTIMAL FACILITY LOCATION PROBLEM IN DISASTER MANAGEMENT AND HUMANITARIAN LOGISTICS

by

Chawis Boonmee

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Engineering

Examination Committee:	Prof. Kimura Katsutoshi Prof. Nakatsugawa Makoto Assoc. Prof. Mikiharu Arimura (Chairman)
Nationality:	Thai
Previous Degree:	Bachelor of Industrial Engineering Chiang Mai University, Thailand Master of Industrial Engineering Chiang Mai University, Thailand
Scholarship Donor:	Ministry of Education, Culture, Sports, Science and Technology Japanese Government (MEXT) Scholarship

Muroran Institute of Technology
Division of Sustainable and Environmental Engineering
Japan

September 2018

ACKNOWLEGEMENT

The author wishes to express his profound gratitude to his advisor, Assoc. Prof. Mikiharu Arimura, for his patient guidance, constructive comments, friendly discussions, enduring supervision, and all valuable efforts for the accomplishment of his study. He is also grateful to Assis. Prof. Takumi Asada, and Assis. Prof. Takumi Asada for their support and for serving as members of his examination committee.

The author also wishes to express his adviser thanks to Assis. Prof. Chompoonoot Kasemset, Assis. Prof. Warisa Wisittipanich, and Mr. Piya Hengmeechai for giving knowledge and recommendation. Great appreciation is also due to the Banta municipality and Banta district at Chiang Rai province, Department of mineral resources, and Natural Disaster Research Unit of Civil Engineering Department of Chiang Mai University (CENDRU) in Thailand for the provision of useful data. I would like to thanks to my family, Ms. Maree Boonmee, Ms. Kingkan Wongmuang, and Mr. Tinn Wongmueng for support and encouragement when I feel downhearted.

Sincere gratitude is extended to the Ministry of Education, Culture, Sports, Science, and Technology for providing the scholarship and the Muroran Institute of Technology for giving the opportunity to study and providing a rewarding experience.

Lastly, the author would like to express his appreciation to all his colleagues especially Sustainable Urban & Transport Laboratory students at the Muroran Institute of Technology for their valuable help and support during his long time stay at Muroran IT

This study is dedicated to the author’s beloved parents whose guidance and support have made it possible for the author to pursue the goals and dreams in his life.

Topic:	A study of optimal facility location problem in disaster management and humanitarian logistics
Author:	Chawis Boonmee
Degree:	Doctor of Engineering
Course:	Course of Advanced Sustainable and Environmental Engineering
Advisor:	Associate Professor Mikiharu Arimura

ABSTRACT

Since the 1950s, the number of disasters has increased continually around the world. This has resulted in enormous problems in human life, economic system, and environment. Owing to those problems, disaster management, and humanitarian logistics issue become an important research for helping at-risk persons to avoid or recover from the effect of the disaster. To enhance and develop the disaster management and humanitarian logistics in facility location problem, this thesis aims to study a disaster management and humanitarian logistics in facility location problem. Facility location problem is one of the problem in disaster management and humanitarian logistics for providing appropriate facility locations in disaster supply chain management such as distribution centers, warehouses, shelters, medical centers, and garbage dumps. This thesis applied an optimization approach in this study in which all of the problems are formulated as a mathematical model with respect to the proposed conceptual models for solving the problem. This thesis proposed four contributions to address and develop in this study that consists of; (1) an integrated multi-model optimization and fuzzy AHP for shelter site selection and evacuation planning, (2) the mathematical programming model for improving evacuation planning and shelter site selection in flood disaster situation, (3) a bi-criteria mathematical optimization model for hierarchical evacuation and shelter site selection under uncertainty of flood events, and (4) a location and allocation optimization model for integrated decision on post-disaster waste supply chain management: on-site and off-site separation for recyclable materials. Furthermore, this also presented a comprehensive review of the existing studies and research gaps on the facility location problems that are related to disaster management and humanitarian logistics. All contributions of this thesis will be a great significance not only in helping policymakers or governors consider and manage the strategic placement of each facility location but also in helping victims during the emergency situation as well.

Keyword: Disaster management, Humanitarian logistics, Facility location problem, Optimization approach, Mathematical model

題目: 人道援助ロジスティクスと災害マネジメントにおける最適施設位置決定問題に関する研究

氏 名: チャウィス　ブーンミー

学位: 博士（工学）

コース: 先端環境創生工学コース

主任指導教員氏名: 有村　幹治 准教授

論文内容の要旨

1950 年代以来、災害の数は世界中で継続的に増加している。これには人命、経済システム、環境に大きな問題をもたらしている。この問題に起因して、災害マネジメント及び人道援助ロジスティクスは、被災者に対する災害の影響の回避、もしくは回復を助けるための重要な研究分野になっている。災害マネジメントと人道援助ロジスティクスの充実と発展のために、本論文では施設配置問題に関する研究を行う。施設配置問題は、災害マネジメントと人道援助ロジスティクスにおける課題の 1 つであり、配送センター、倉庫、シェルター、医療センター、廃棄場等の災害サプライチェーン管理における施設位置を適切に決定する問題である。本論文では、この問題の解決のために、施設配置に関するコンセプトモデルを提案し，全てのモデルを数学モデルとして定式化したうえで，各種の最適化手法の適用を行った。本論文は、施設配置問題に関する以下の課題、（1）避難地選択と避難計画立案のための統合型多目的最適化とファジィ AHP の適用、（2）洪水災害時の避難計画と避難地選択改善のための数学プログラミングモデル、（3）不確実性を考慮した階層的避難と避難地選択のための二基準数学最適化モデル、（4）災害後の廃棄物サプライチェーンマネジメントにおける意思決定支援のための施設配置場所と配分の統合型最適化モデルの提案、から構成される。また、災害マネジメント及び人道援助ロジスティクスに関連する施設配置問題に関する既存研究の包括的レビューを行った。本論文の全成果は、政策立案者や行政担当者の戦略的施設配置の検討、管理を支援するだけではなく、緊急時の被災者の援助についても大きく寄与する。

キーワード：災害マネジメント、人道援助ロジスティクス、施設位置決定問題、最適化手法、数学モデル

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	Definition
AHP	Analytic Hierarchy Process
CDA	Combined Distribution and Assignment
CENDRU	The of Civil Engineering Natural Disaster Research Unit
CI	Consistency Index
CR	Consistency Ratio
DE	Differential Evolution
DM	Disaster Management
DMC	Disaster Management Cycle
DOM	Disaster Operation Management
EA	Evolutionary Algorithm
EI	Expected Interval
ELECTRE	ELimination Et Choix Traduisant la REalité
EV	Expected Value
FEMA	Federal Emergency Management Agency
FLP	Facility Location Problems
HADC	Humanitarian Aid Distribution Centers
HL	Humanitarian logistics
LGP	Lexicographic Goal Programming
LP	Linear Programming
MCDM	Multiple Criteria Decision Making
MCLP	Maximal Covering Location Problems
MILP	Mixed Integer Linear Programming
MINLP	Mix Integer Non-Linear Programming
OR/MS	Operation Research/Management Science
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PSO	Particle Swarm Optimization
PTF	Pick-the-Farthest
PWSCM	Post-disaster Waste Supply Chain Management
QGIS	Quantum Geographic Information System
RI	Relative Improvement
RLC	Relief Logistic Center

Abbreviation	Definition
RSR	Reduction, Separation and Recycling
TDSR	Temporary Disposal and Storage Reduction
TDWCSC	Temporary Disaster Waste Collection and Separating Centers
TDWPRC	Temporary Disaster Waste Processing and Recycling Centers
THB	Thai Baht
TLGP	Two-step Logarithmic Goal Programming
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VNS	Variable Neighborhood Search
WHO	World Health Organization

Chapter 1
Introduction

1.1 Background

Disaster management (DM) is the organization and management of resources and responsibilities for dealing with all humanitarian aspects of emergencies, in particular mitigation, preparedness, response and recovery in order to relief, reduce, or avoid the impact of disasters [1]. The goals of DM can segregate into three points [2]; (1) reduce, or avoid, losses from hazards; (2) assure prompt assistance to victims; (3) achieve rapid and effective recovery. DM activities are conducted across four consecutive stages: mitigation, preparation, response, and recovery which is known as "Disaster management cycle (DMC)", is illustrated in Figure 1.1. The DMC illustrates the ongoing operation in which governments plan for and reduce the effect of disaster through pre-disaster and post-disaster. The benefit of suitable actions at all activities in the DMC lead to greater preparedness, better warnings, reduced vulnerability or the prevention of disaster, and reduced loss of human life and economic system. In mitigation stage, this aims to minimize the impacts of disaster. The activity in this stage includes the building codes; vulnerability analyses updates; zoning and land use management; building use regulations and safety codes; preventive health care; and public education. In preparedness stage, this is planning activities to be conducted following disaster occurrence that increase chances of survival and minimize financial and other losses. The purposes of this stage aim to enhance by having response procedures and mechanisms, developing short-term and long-term strategies, public education, building efficient warning systems and planning about humanitarian logistics including food, water, medicines and other essentials. Preparedness stage measures include preparedness plans, emergency drill, emergency communications systems, evacuations training; inventory strategies and public educations. In response stage, the goals of this stage aim to provide immediate assistance and reduce the effect of disasters during their aftermath to prevent additional suffering, financial loss, or other losses. Such assisting refugees with transport, shelter, consumer goods should be strongly provided in this stage. In recovery stage, this aims to restore the affected area back to a normal situation after the disaster. Recovery stage measures include temporary housing, debris, health and safety education, and reconstruction. Humanitarian logistics is one of operation that is involved to following three stages in DM activities: preparation, response, and recovery. Humanitarian logistics (HL) is the process of planning, implementing and controlling the efficient, cost effective flow and storage of goods and materials, meanwhile collecting information from the point of origin to point of consumption for purpose of relieving the sufferings of vulnerable people.

Since the 1950s, the number and severity of disasters have exponentially increased, with the number of affected people, loss of human life, and loss of economic system having increased in proportion as shown in Figure 1.2. In 2016, 315 naturally triggered disasters were recorded, with the economic damages estimated to be US$ 210 billion, resulting in the deaths of 8,250 people [3]. Owing to an increasing number of disasters, many researchers have paid a great deal of attention to the concept of DM with humanitarian logistics, with the objective of helping at-risk persons to avoid and recover from the effects of a disaster [4]. Optimization, decision making, and simulation being proposed as the main approaches in DM and HL, especially the optimization approach is one tool that has tended to apply in disaster research to solve the problems of disaster planning and humanitarian logistics. Optimization approach is find an alternative with the highest achievable performance under the provided conditions by minimum undesired criteria or maximum desired ones. The optimization technique will reformulate the problem in form that is convenient for analysis in which it can describes the problem much more concisely. This tends to make the overall structure of the problem more comprehensible, and it helps to reveal important cause-and-effect relationships. In this way, it indicates more clearly what additional data are relevant to the analysis. It also facilitates dealing with the problem in its entirety and considering all its interrelationships simultaneously.

Facility location problems involving the location and selection of distribution centers, warehouses, shelters, medical centers, and other locations are an important approach in DM and HL. Facility location modeling is an approach to strategic planning design for pre- and post-disaster operations and is important for effective and efficient DM and HL planning [5].

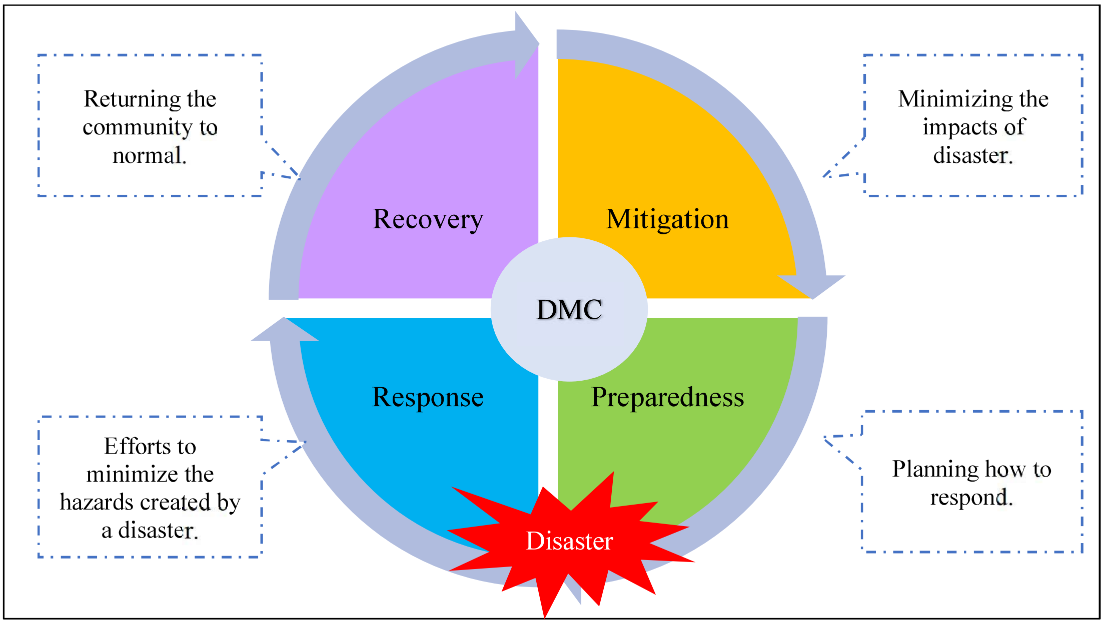


Figure 1.1 The disaster management cycle (DMC) [2]

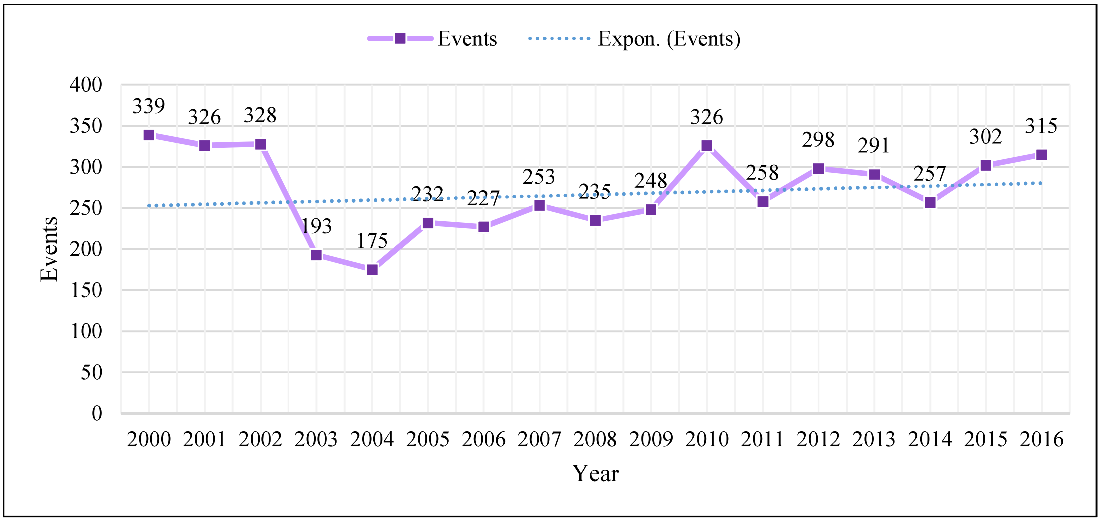


Figure 1.2 Total natural disaster events [3]

In recent research, emergency humanitarian logistics optimization models have been emphasized as an important element in disaster facility location problems. Some problems with regard to facility location problem and some research gaps in DM and HL still need to enhance and develop.

According to the above mentions, this thesis aims to enhance and develop the disaster management and humanitarian logistics in facility location problem in which the optimization approach is applied to solve in this research. The remainder of this chapter is organized as follows: section 1.2 presents objectives and research questions. Section 1.3 presents methodologies and contributions. Ultimately, outline of dissertation is presented in section 1.4

1.2 Objectives and Research Questions

From the above mention, the disaster management still needs to improve and develop for augmenting efficiency of disaster management thought supply chain. Although this field is widely known, it still has some research gaps in the disaster management and humanitarian logistics. The main objective of this research is:

"To augment the efficiency disaster management and humanitarian logistics in facility location problem though optimization approach"

To achieve the aim of this research, then many questions arisen. The research questions are described as follows;

Main question 1: How to improve or develop the disaster management and humanitarian relief logistics in facility location problem for the efficient operations?

Sub Question 1. What is the main problem or research gap of the disaster management and humanitarian relief logistics in facility location problem?

Sub Question 2. What is the benefit of improvement and development?

Main question 2: How the optimization approach can apply in facility location problem of disaster management and humanitarian relief logistics?

Sub Question 1. What the minor approach can apply in optimization approach?

According to the questions of this research, this research will select the problem that should improve and develop in the disaster management and humanitarian relief logistics. The frameworks, mathematical optimization models and solution methods are proposed with respect to the different problem in each facility location problem. Each problem will be solved associate with the other relevant problem. The main advantage of this research will be a great significance not only in helping policymakers or governors consider the spatial aspect of the strategic placement of each facility location problem but also in helping victims during the emergency situation as well.

1.3 Methodologies and Contributions

The mechanism of this research is illustrated in Figure 1.3. A comprehensive analysis of disaster management and humanitarian logistics is examined in the first part in which it is represented in Chapter 2. This section aims to conduct a survey on the facility location problems that are related to disaster management and humanitarian logistics based on both data modeling types and problem types and to examine the pre- and post-disaster situations with respect to facility location, such as the location of distribution centers, warehouses, shelters, debris removal sites and medical centers. Moreover, research gaps will be identified and be addressed in further research studies to develop more effective disaster relief operations in which all perspectives are addressed such as environment, economics, risk, process or system, information, etc. After that the problems are selected for solving, each facility location is identified the problems and research gaps. Each problem is represented into different chapters that presents in Chapter 3 – Chapter 6. Each chapter in this research is analyzed and identified the problem. The conceptual model or framework is designed for solving those problems. After the conceptual model is formulated, the mathematical model is formulated base on optimization approach and some tools are chosen to apply to in the solution method such as Epsilon Constrain, Fuzzy Approach, Analytic hierarchy Process (AHP), Particle Swarm Optimization (PSO) and Differential Evolution (DE). Then, the conceptual model will be validated by some case study for evaluating the efficiency of solution approach. Finally, the conclusions and discussions are presented.

The contributions of this research are summarized according to results of different chapters are as follow:

1. The existing studies and research gaps on the facility location problems that are related to disaster management and humanitarian logistics. (Chapter 2)
2. An integrated multi-model optimization and fuzzy AHP for shelter site selection and evacuation planning. (Chapter 3)
3. The mathematical programing model for improving evacuation planning and shelter site selection in flood disaster situation. (Chapter4)
4. A bi-criteria mathematical optimization model for hierarchical evacuation and shelter site selection under uncertainty of flood events. (Chapter 5)
5. Location and allocation optimization model for integrated decision on post-disaster waste supply chain management: on-site and off-site separation for recyclable materials. (Chapter 6)

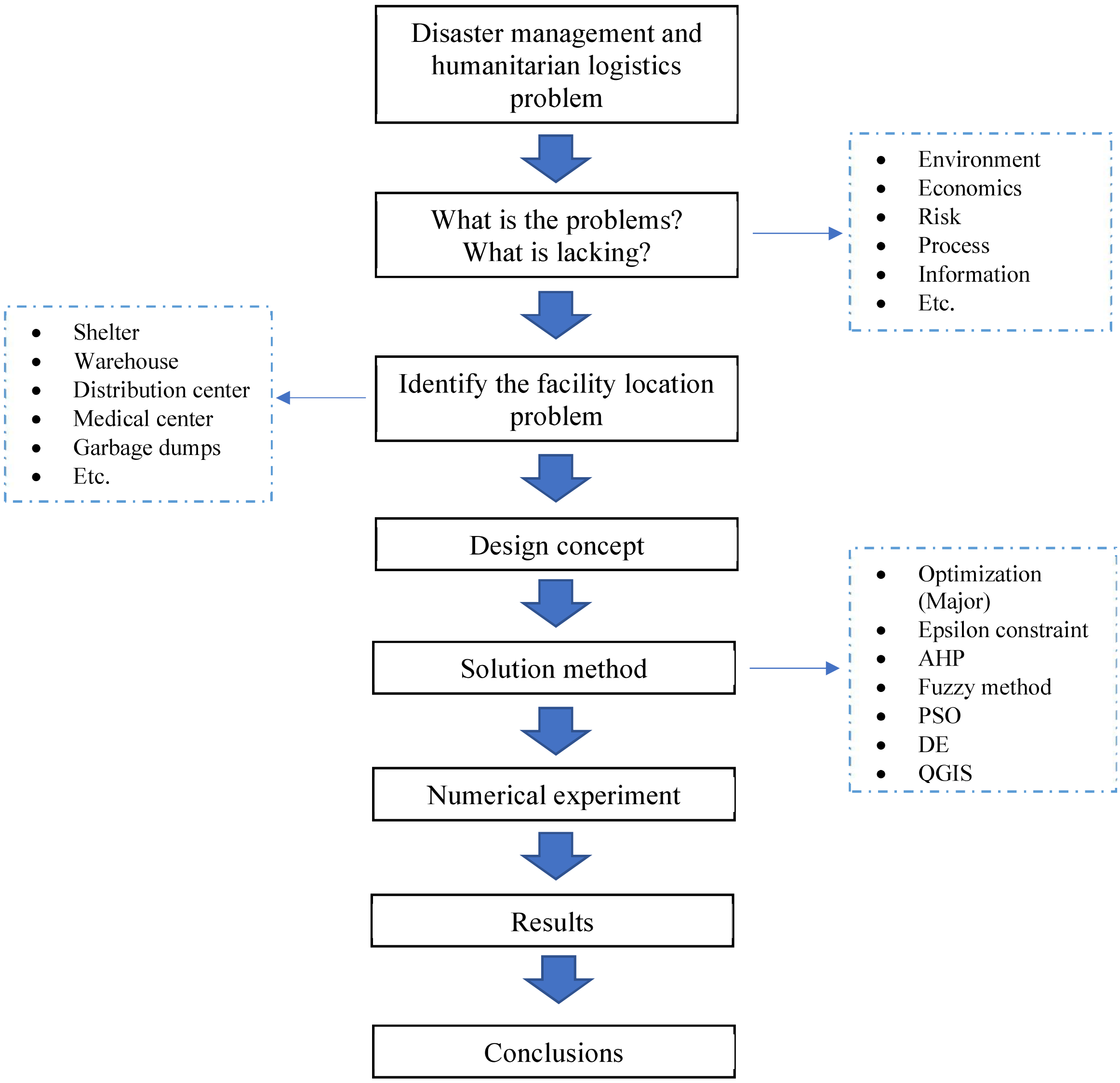


Figure 1.3 Conceptual framework

1.4 Outline of Dissertation

This research consists of eight chapters. Following the introduction chapter, remainder of this research is organized as below.

Chapter 2 gives a literature review of key concepts in facility location problem in disaster management and humanitarian logistics. Since the 1950s, the number of natural and man-made disasters has increased exponentially and the facility location problem has become the preferred approach for dealing with emergency humanitarian logistical problems. To deal with this challenge, an exact algorithm and a heuristic algorithm have been combined as the main approach to solving this problem. Owing to the importance that an exact algorithm holds with regard to enhancing emergency humanitarian logistical facility location problems, this chapter aims to conduct a survey on the facility location problems that are related to emergency humanitarian logistics based on both data modeling types and problem types and to examine the pre- and post-disaster situations with respect to facility location, such as the location of distribution centers, warehouses, shelters, debris removal sites and medical centers. The survey will examine the four main problems highlighted in the literature review: deterministic facility location problems, dynamic facility location problems, stochastic facility location problems, and robust facility location problems. For each problem, facility location type, data modeling type, disaster type, decisions, objectives, constraints, and solution methods will be evaluated and real-world applications and case studies will then be presented. Finally, research gaps will be identified and be addressed in further research studies to develop more effective disaster relief operations.

Chapter 3 shows an integrated multi-model optimization and fuzzy AHP for shelter site selection and evacuation planning. Due to an increasing severity of recent disasters, shelter site selection and evacuation planning have become an essential function for the purpose of helping at-risk persons to avoid or recover from the effect of a disaster. Therefore, this chapter aims to propose an integrated mathematical optimization and fuzzy analytic hierarchy process for shelter site selection and evacuation planning. The mathematical models are formulated under different constraints and model types, in which the objective of each mathematical model is to minimize the total travel distance. The mathematical models are coded and run in optimizer tool for creating plans. Then, Fuzzy Analytic Hierarchy Process is applied to choose the appropriate plan under uncertainty and vagueness of the expert's opinion. A numerical example with a real case study of a Banta municipality in Thailand is given to demonstrate the application of our conceptual model. This chapter will be great significance in helping decision makers consider placement of emergency shelters and evacuation planning with respect to both qualitative and quantitative measurement. Moreover, this chapter can be a guide of the methodology to be implemented to other problems as well.

Chapter 4 presents improving evacuation planning and shelter site selection for flood disaster. Evacuation planning and shelter site selection are the most important function of disaster management for the purpose of helping at-risk persons to avoid or recover from the effect of a disaster. This chapter aims to propose a stochastic linear mixed-integer mathematical programming model for improving flood evacuation planning and shelter site selection under a hierarchical evacuation concept. The hierarchical evacuation concept is applied in this study that balances the preparedness and risk despite the un-certainties of flood events. This study considers the distribution of shelter sites and communities, evacuee's behavior, utilization of shelter and capacity restrictions of the shelter by minimizing total population-weighted travel distance. This chapter conducts computational experiments to illustrate how the proposed methodical model works on a real case problem in which this chapter proposed Thai flooding case study. Also, this chapter performs a sensitivity analysis on the parameters of the mentioned mathematical model and discuss our finding. This study will be a great significance in helping policymakers consider the spatial aspect of the strategic placement of flood shelters and evacuation planning under uncertainties of flood scenarios.

Chapter 5 represents the developed research from the chapter 4. This chapter proposes a stochastic linear mixed-integer programming model for flood evacuation planning to optimize decision related to shelter site selection under a hierarchical evacuation concept and probabilistic scenarios. The proposed model considers two criteria as objective function: travel distance and risk index of shelter. This chapter not only provides flood shelters and distribution of communities but also determines hierarchical evacuation concept, evacuee's behavior, financial constraint, and uncertainty of flood events. Since problem is formulated, the epsilon constraint approach is selected to solve this problem. This chapter validates the mathematical model by generating a base case scenario using numerical data for Chiang Mai, Thailand. The results are proposed and discussed which represent several alternatives to decision makers. This chapter will be great significance in helping decision makers consider the spatial aspect of the strategic placement of flood shelters and flood evacuation planning under uncertainty of flood scenarios.

Chapter 6 deals with the issue of post-disaster waste supply chain management. Since the 1950s, the number of disasters has increased continually around the world. This has resulted in enormous amounts of waste in post-disaster situations and this can have a serious impact on the environment. Post-disaster waste management is one of the most important operational management systems that have been developed to help affected communities recover and restore conditions back to a stable situation after a disaster. Hence many researchers have paid a great deal of attention to this problem with an aim to overcome these challenges. Location and allocation optimization have become the preferred approach for dealing with post-disaster waste management problems. In addressing this situation, this chapter aims to present the developed system of post-disaster waste supply chain management strategy (PWSCM) along with the integrated decision-making system for the on-site and off-site separation of recyclable materials. A mathematical model of mixed-integer linear programming is proposed in which the objective aims are to minimize the financial effects through assessment of the fixed costs and variable costs, RSR, and the penalty costs associated with the negative environmental and human effects of post-disaster scenarios and to maximize revenue from any sellable waste. The proposed model considers all networks in the debris operation process that consists of waste collection and separation sites, processing and recycling sites, disposal sites and market sites. Moreover, the RSR technologies have also been considered in the proposed model. The output of this study will be the determination of locating the appropriate temporary waste collection sites, processing sites, and landfills, and to facilitate debris flow decisions. Due to the limitations of competence of an exact solution method for such a large problem for which it is difficult to achieve acceptable results in a reasonable time, this study also presents two effective metaheuristic approaches with particular encoding and decoding schemes; Particle Swarm Optimization (PSO) and Differential Evolution (DE) to solve PWSCM. To illustrate the performance of the algorithms, the numerical results in small-, medium-, large- and very large-sized problems were evaluated and compared with a set of certain generated problems. The results showed that, for the very large-sized problem, there was a level of superiority associated with the proposed algorithm by PSO to DE and the exact solution method. Finally, the numerical tests for PWSCM improvement will be discussed. The performance of the proposed PWSCM improvement system was superior to both the on-site separation model and the off-site separation model.

Finally, Chapter 7 provided the summary of the difference tasks in this research, presents the conclusions along with some point for direction of the research.

The outline of flow of the research is illustrated in Figure 1.4 Below.

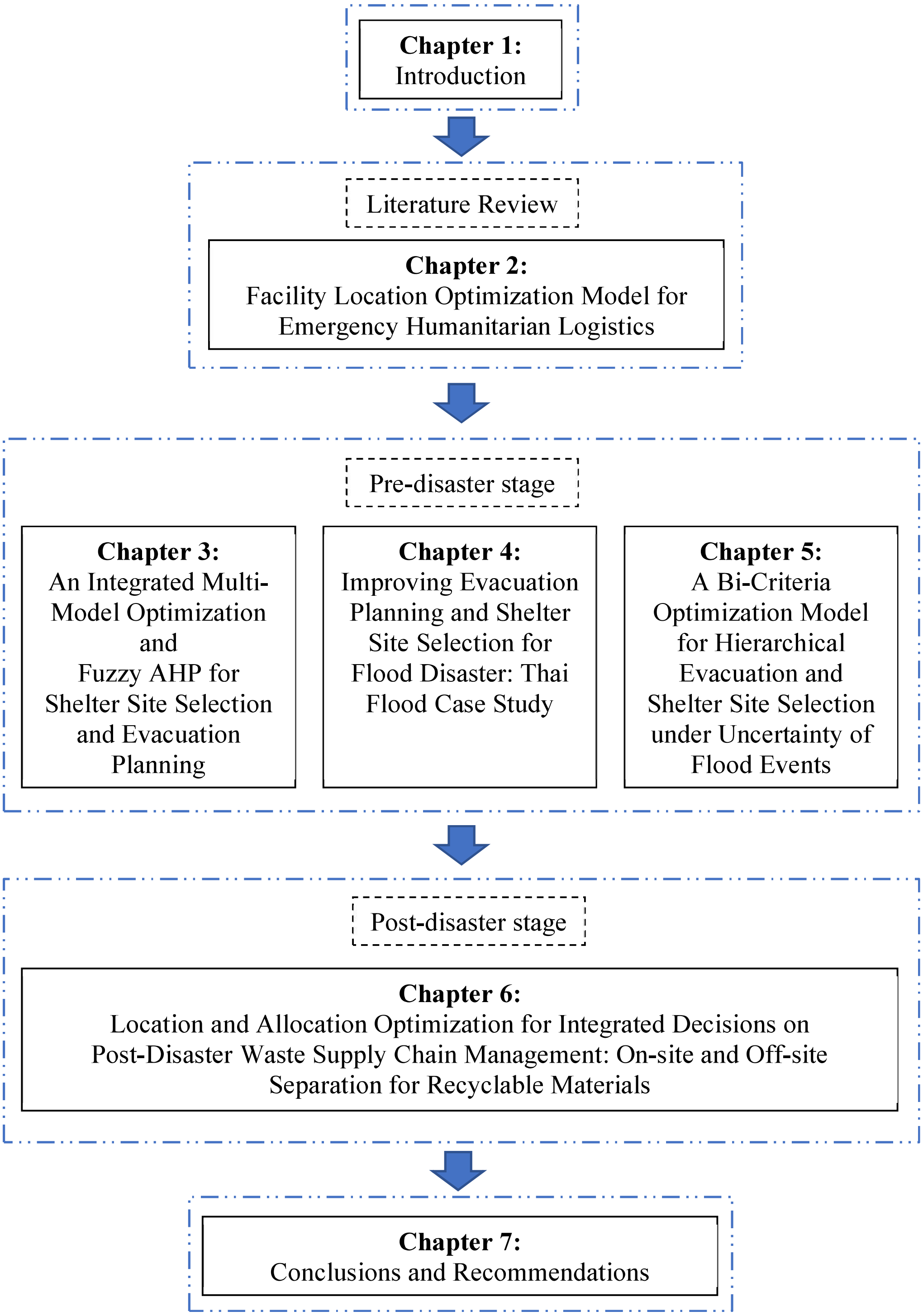


Figure 1.4 Research outline

1.5 References

[1] International Federation of Red Cross and Red Crescent Societies, [Online]. Available: http://www.ifrc.org/en/what-we-do/disaster-management/about-disaster-management. [Accessed 20 December 2017].

[2] Urban Evironmental Management, https://www.gdrc.org/uem/disasters/1-dm_cycle.html. [Accessed 21 December 2017].

[3] Impact Forecasting, 2016 Annual Global Climate and Catastrophe Report. [Online]. Available: http://thoughtleadership.aonbenfield.com/Documents/20170117-ab-if-annual-climate-catastrophe-report.pdf. [Accessed 22 December 2017].

[4] Lehtveer, M., & Hedenus, F. (2015). Nuclear power as a climate mitigation strategy–technology and proliferation risk. Journal of Risk Research, 18(3), 273-290.

Chapter 2

Facility Location Optimization Model for Emergency Humanitarian Logistics

2.1 Introduction

Since the 1950s, both the number and magnitude of disasters have been continuously increasing, with the number of affected people having increased in proportion (about 235 million people per annum on average since the 1990s). In 2014, 324 natural disasters were recorded, with economic damages estimated to be US$ 99.2 billion [1]. According to the International Disaster Database, Asia and the Americas have been the continents most affected by disasters such as floods, earthquakes, storms, and landslides [2]. Disaster is any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area [3]. Such situations may include natural disasters such as drought, earthquakes, floods or storms, and epidemics, or man-made disruptions such as nuclear or chemical explosions [4-6]. According to the increasing number of disasters, many academicians have paid more attention to “Disaster management (DM)” for helping at-risk persons to avoid or recover from the effect of the disaster [7]. DM activities are conducted across four consecutive stages: mitigation, preparation, response, and recovery. Coppola [8] defined mitigation as reducing the probability of disaster occurrence and decreasing the degree of the hazard; furthermore, he defined preparation as planning activities to be conducted following disaster occurrence that increase chances of survival and minimize financial and other losses. Response was defined as reducing the impact of disasters during their aftermath to prevent additional suffering, financial loss, or other losses. Finally, recovery was defined as restoring the affected area back to a normal situation after the disaster. Disaster situations can be divided into two stages: a pre-disaster or proactive (mitigation and preparation) stage and a post-disaster or reactive (response and recovery) stage. Humanitarian logistics is one of operation that is involved to following three stages in DM activities: preparation, response, and recovery. Humanitarian logistics (HL) is the process of planning, implementing and controlling the efficient, cost effective flow and storage of goods and materials, meanwhile collecting information from the point of origin to point of consumption for purpose of relieving the sufferings of vulnerable people [9-10].

Because of the increasing severity of recent disasters, research has paid more attention to DM dealing with humanitarian logistics, with optimization, decision making, and simulation being proposed as the main approaches. Disaster research has tended to employ modeling and optimization to solve emergency humanitarian logistics problems. Labib and Read [11] proposed a hybrid model for learning from failures that examined the multifaceted nature of disaster research and the hybrid modeling approaches within this domain and tested a reliability framework and multiple-criteria decision analysis techniques on the 2005 Hurricane Katrina disaster. Verma and Gaukler [12] proposed a deterministic and stochastic model for the pre-positioning of disaster response facilities at safe locations and demonstrated its usefulness with a case study on a Californian earthquake. Scott [13], Kongsomsaksakul et al. [14], Mete and Zabinsky [15], Salman and Yücel [16], Bayram et al. [17], Marcelin et al. [18] and Jabbarzadeh et al. [19] also studied emergency humanitarian logistics’ facility location problems.

Recent research has also included surveys on effective DM. Altay and Green [20] reviewed the disaster operation management (DOM) in which this article focuses on lifecycle phase. Then, Galindo and Batt [21] extended the article of Altay and Green [20] with new advance and presented an original evaluation about the most common assumptions in OR/MS research in DOM. Caunhyeet et al. [22] reviewed an optimization model for emergency logistics that was classified into three main categories: (1) facility location, (2) relief distribution and casualty transportation and (3) other operation. Each literature is analyzed and structured based on the goals, constraints, data modelling type, and decisions. Safeer et al. [23] surveyed the modeling parameters for the objective functions and constraints in humanitarian logistics distribution that classified into two terms: casualty transportation and evacuation and relief distribution. Özdamar and Ertem [2] presented a survey that focused on the response and recovery planning phases of the disaster lifecycle. This article classified in terms of vehicle/network representation structures and their functionally. The review structured based on objectives, constraints, structures of available mathematical model and solution methods. Furthermore, information systems in humanitarian logistics was also presented. Anaya-Arenas et al. [24] proposed systematic review of contributions related the relief distribution networks in response to disasters by categorizing them according to location and network design, transportation, location and transportation, and other important topics. Zheng et al. [25] studied research advances in evolutionary algorithms for disaster relief operations. The research is classified into five categories and represented the summary of related papers on evolutionary algorithms for solving the problem. Habib et al. [9] reviewed mathematical model in humanitarian logistics by covering all the phases of disaster, and provided the summary of modelling techniques and solution methodologies.

Facility location models involving the location and selection of distribution centers, warehouses, shelters, medical centers, and other locations are an important approach in DM. Facility location modeling is an approach to strategic planning design for pre- and post-disaster operations and is important for effective and efficient DM planning. In recent research, as noted above, emergency humanitarian logistics optimization models have been emphasized as an important element in disaster facility location problems. To overcome this challenge, two approaches can solve this problem, (1) heuristic algorithm and (2) exact algorithm. Normally, the emergency humanitarian logistics' facility location problems are NP-hard, most researches are usually solved by heuristic algorithm because it can solve with less time and can solve complicated problem, but the result of this approach is poor quality when compare with exact algorithm. Although the first approach is overcome the second approach, but the second approach is necessary to use for checking the heuristic algorithm, and moreover some case can be solved by exact algorithm as well. Hence exact algorithm is important to learn unavoidably.

Following on from this previous research, emergency humanitarian logistics' facility location problems are lacking a literature review based on data modelling types and problem types that is basic element of exact algorithm for enhancing or developing humanitarian logistics problem. Therefore, this chapter aims to propose a survey of research work on emergency humanitarian logistics' facility location optimization model based on data modelling types and problem types. Not only to survey this research, but also to present basic mathematical models simultaneously for introducing interested people to discipline. Moreover, each literature is analyzed and structured based on objectives, conditions, disaster types, facility location types, data modelling types, applications, solution methods, categories, and case studies. Finally, research gaps and future research possibilities are then identified.

The remainder of this chapter is organized as follows: Section 2.2 presents the scope of the literature review. In Section 2.3, facility location models are classified into four categories: deterministic, stochastic, dynamic, and robust. Section 2.4 presents an application and case study. In Section 2.5 future research that illuminates the research gaps is presented along with a framework analysis. Finally, a conclusion is given in Section 2.6.

2.2 Scope of literature review

In this chapter, emergency humanitarian logistics' facility location optimization models are examined. To develop the literature database, emergency humanitarian logistics' facility location optimization models were searched for in journals, books, and conference proceedings and then classified according to the facility location problem and optimization method categories: deterministic, stochastic, dynamic, and robust. Finally, applications and case studies were reviewed. Journal search engines such as the transport research board publication database, the IEEE database standard, Science direct, and the Springer journal database were interrogated using "disaster," "facility location," "humanitarian logistics," "optimization model," and "emergency" as the key search strings. Further, the references in each paper, including books and conference proceedings, were scrutinized to reveal any additional relevant papers. Most articles identified in the literature search came from a range of journals: Social-Economic Planning Science, European Journal of Operations Research, Computers & Industrial Engineering, Applied Soft Computing, Expert Systems with Applications, Transportation Research Part B and Part E, Computer & Operation Research, Int. J. Production Economics, Journal of Cleaner Production, the Journal of Risk Research, and the Journal of the Eastern Asia Society for Transportation Studies.

2.3 Literature breakdown and analysis

From a general viewpoint, Arabani and Farahani [26] found that facility location problems could be defined across the two elements of space and time, in which space was "a planning area where facilities are located," and time was "the time the location is identified" (developing a new facility or revising an existing facility). Essentially, however, space and time should be analyzed concurrently. Emergency humanitarian logistics' facility location problems included the identification of locations such as fire stations, emergency shelters, distribution centers, warehouses, debris removal sites and medical centers. Potential facilities were identified based on the geography of the respective areas and divided into two: continuing facility location problems (facilities located in the planning areas) and discrete facility location problems (facilities located in candidate locations) [26]. Most facility emergency humanitarian logistics' location optimization models were combined with other logistics problems such as stock pre-positioning, relief distribution, casualty transportation, evacuation planning, resource allocation, commodity flows, and other operations [22]. Facility location optimization models are usually based on mixed integer linear programming (MILP) with binary location variables. Most reviewed models were single level and the least reviewed models were bilevel. Emergency humanitarian logistics' facility location optimization models varied depending on (1) facility location planning objectives, (2) the situation (certainty, uncertainty, and data risk), (3) duration (short term or long term), (4) the number of locations, (5) the service pattern, and (6) the commodity types required.

From the surveyed models, the factors that affected the mathematical model and solution methods were first examined. To expedite this process, the models were separated based on data modelling types and problem types: deterministic facility location problems, stochastic facility location problems, dynamic facility location problems, and robust facility location problems.

2.3.1 Deterministic facility location problems

Deterministic facility location problems are used to select or locate shelters, distribution centers, warehouses, and medical centers by determining the place and input parameters such as the possible number of individuals affected, the location, shelter capacity, transportation costs, and fixed cost, with all parameters being known and constant over time. This problem formed the basis for the dynamic, stochastic, and robust models. Deterministic facility location problems can be separated into four different types.

1. Minisum facility location problem

This problem selects or locates P facilities (the maximal number of facilities that can be placed) and seeks to minimize the total transport distance (including transport time or transport cost) between the demand points and selected facilities. The formulation for this mathematical model is as follows [27, 28]:

Indices and Index sets

I Set of demand nodes; $i \in I$

J Set of facility sites; $j \in J$

Decision variables:

X_j = 1 if a facility is located at eligible site j, and 0 otherwise.

Y_{ij} = 1 if facility j services demand point i, and 0 otherwise.

Input parameters:

d_{ij} the distance between demand point i and candidate facility j

cap_j the capacity of facility j

P the maximal number of facilities that can be placed

w_i the weight associated to each demand point (demand or number of customers / people)

Minimize
$$\sum_i \sum_j w_i d_{ij} Y_{ij} \tag{2.1}$$

Subject to
$$\sum_j X_j = P \tag{2.2}$$

$$\sum_j Y_{ij} = 1 \qquad \forall i \tag{2.3}$$

$$\sum_i w_i Y_{ij} \le cap_j X_j \qquad \forall j \tag{2.4}$$

$$X_j, Y_{ij} \in \{0,1\} \qquad \forall i, \forall j \tag{2.5}$$

The objective function (equation (2.1)) minimizes the total distance between the demand points and candidate facilities. Equation (2.2) states that there are P facilities to be located at site j. Equation (2.3) ensures that each demand point i is assigned to facility j. Equation (2.4) allows assignment only to sites where facilities are located and ensures that the capacity at each located facility is not exceeded. Equation (2.5) sets binary conditions for the model variables. If the capacity at facility j is unlimited, equation (2.4) can be replaced with equation (2.6).

$$Y_{ij} \leq X_j \qquad \forall i, \forall j \qquad (2.6)$$

The distance function is generally identified as rectilinear, Euclidean, or squared Euclidean. However, emergency humanitarian logistics problems consider distance to be the actual distance between the demand points and the facilities. Therefore, d_{ij} is defined as an actual distance and a constant (no distance function). This problem, known as the P-median, was developed by Hakimi [27]. Since that time, it has been widely applied to emergency facility location problems. McCall [29] developed a mathematical model with the prepositioning of assistance pack-up kids during disaster that aims to minimize victim nautical miles and shortages. Verma and Gaukler [12] proposed a deterministic model and a stochastic model that explicitly considered the impact a disaster could have on disaster response facilities and population centers in the surrounding areas. The deterministic model estimated the expected transportation costs over all disaster scenarios and assumed that the costs were linear and depended on the distance to be traveled and the supplies to be shipped. The proposed model was tested using data from a Californian earthquake. According to relief warehouse, Horner and Downs [30] proposed a warehouse location model for locating the relief goods to affected zones that minimize the cost of distributing of relief goods. Others related relief warehouse was proposed by Lin et al [31] and Hong et al. [32]. To formulate multi-objective model or multi-criteria model. Abounacer et al. [33] proposed a multi-objective location-transportation model for disaster response with the aim of determining the number, position, and mission of the required humanitarian aid distribution centers (HADC) within a disaster region. The identified objectives were to minimize total transportation duration from the distribution centers to the demand points, minimize the number of agents (first-aiders) needed to open and operate the selected distribution centers, and minimize the non-covered demand for all demand points within the affected area. Barzinpour and Esmaeili [34] proposed a multi-objective relief chain location distribution model for urban disaster management. This model was developed for preparation phase which considers both humanitarian and cost-based objectives in a goal-programming approach. Similarly, Ransikarbum and Mason [35] presented multiple objective, integrated network optimization model for making strategic decisions in the supply distribution and network restoration phases during post-disaster management. The proposed model determined fairness/equity based solutions under constrain of capacity, resource limitations and budget. The objective functions consist of maximizing equity or fairness, minimizing total unsatisfied demand, and minimizing total network cost. In multi-level optimization, Kongsomsaksakul et al. [14] presented an optimal shelter location model for flood evacuation planning using bilevel programming to minimize total evacuation time (the upper-level problem) and to choose destinations (shelter), and evacuation routes (the lower-level problem). The combined distribution and assignment (CDA) model was adapted to a lower-level problem, with the bilevel programming being solved with a genetic algorithm. Marcelin et al. [18] proposed a p-median based modeling framework linked to a geographic information system for providing people with hurricane disaster relief that aimed to minimize the total demand weighted travel costs between each neighborhood and the nearest relief facility. Moreover, Irohara et al. [36] developed tri-level programming model for disaster preparedness planning. The facility location and inventory pre-positioning decisions are proposed in the top level of the model while the second level determines the damage inflicted by the disaster and the third level considers response and recovery decisions, respectively. The proposed model was validated with a case study on hurricane preparedness in southeast USA by using a dual-ascent approach.

2. Covering problem

The covering problem has been applied to wide range of emergency humanitarian logistics' facility location problems [37]. The objective of the covering problem is to cover the demand points within distance or time limits. Normally, this problem is suitable for hospitals, fire stations and shelter site.

A. Set covering problem

The set covering problem deals with site selection and aims to minimize the total number of facilities or the total fixed cost of open facilities by covering all demand points. The formulation for the set covering problem is as follows [37]:

Input parameters (addition):

c_j fixed cost of facility j

L_i distance limit within which a facility can service demand point i

N_i the set of eligible facility sites located within the distance limit and that are able to service demand point i ($N_i = \{j \mid d_{ij} \le L_i\}$)

Minimize $$\sum_j c_j X_j \tag{2.7}$$

Subject to $$\sum_{j \in N_i} X_j \ge 1 \qquad \forall i \tag{2.8}$$

$$X_j \in \{0,1\} \qquad \forall j \tag{2.9}$$

Equation (2.7) is the objective for the set covering problem, which is to minimize the total fixed cost of opening facilities or the total number of facilities. Equation (2.8) ensures that all demand points are assigned to at least one selected facility within the distance limit. Equation (2.9) defines the binary variables in the model.

Toregas et al. [37] first proposed the set covering problem for emergency humanitarian logistics with the aim of minimizing the total number of facilities needed to cover all demand points. Dekle et al. [38] and Ablanedo- Rosas et al. [39] used a set covering problem for an emergency medical center location problem. Hale and Moberg [40] formulated a deterministic set covering problem and a four-step secure site decision process, in which the proposed model secured the site locations presented in step four by identifying the minimum number and possible locations for off-site storage facilities. Similarly, Dekle et al. [38] proposed a set covering model for covering of demand in the disaster target zone that aims to locate the disaster recovery centers in pre-disaster context. Hu et al. [41] presented a mathematical model for enhancing earthquake shelter location selection and the districting planning of service areas jointly that aims to minimize the total travel evacuation distance and total cost. The second objective was formulated from set covering problem. Finally, they proposed a non-dominated sorting genetic algorithm for solving the proposed mathematical model. Aksen and Aras [42] proposed a bilevel fixed-charge location problem, in which the defender (upper level) sought to locate and operate a set of facilities and the attacker (lower level) aimed to maximize the accessibility costs both capacity expansion costs and post-attract demand-weight travelling costs. Abounacer et al. [33] studied a multi-objective emergency location-transportation problem that had three main objectives, one of which was a set covering problem that sought to minimize the total number of agents needed to operate the open HADC.

B. Maximal covering problem

The maximal covering problem designates site selection as P facilities and focuses on maximizing the total number of demand points covered within the distance limitations. The formulation is as follows [43]:

Decision variables (addition):

Z_i = 1 if demand point i is covered by a facility within S distance, and 0 otherwise.

Maximize $$\sum_i w_i Z_i \qquad (2.10)$$

Subject to $$\sum_{j \in N_i} X_j \geq Z_i \qquad \forall i \qquad (2.11)$$

$$\sum_{j \in N_i} X_j = P \qquad (2.12)$$

$$X_j, Z_i \in \{0,1\} \qquad \forall i, \forall j \qquad (2.13)$$

The objective is to maximize the total number of demand points covered within the distance limitations (equation (2.10)). Equation (2.11) ensures that demand point i is assigned to a selected facility, and also ensures that all facilities assigned to demand point i are located within the given distance limit. Equation (2.12) states that there are P facilities to be located in the eligible facility location. Equation (2.13) defines the binary variables in the model.

Both the set covering problem and the maximal covering problem are integer linear programming problems. Church and Velle [43] developed constraint (2.10), which was reformulated as the following equation (2.14), in which the objective function aimed to minimize the number of uncovered demand points within a maximal service distance. Equations (2.14) and (2.15) were derived by substituting $\overline{Z}_i = 1 - Z_i$ and also by following equations (2.16) and (2.17) that are the same constraints as explained for equations (2.12) and (2.13), respectively. The new formulation was utilized in solving this problem using linear programming (LP).

Decision variables (Addition):

$\overline{Z}_i$ = 1 if demand point i is not covered by a facility within S distance,

and 0 otherwise.

Minimize $\sum_{i} w_i \overline{Z}_i$ (2.14)

Subject to $\sum_{j \in N_i} X_j + \overline{Z}_i \geq 1 \quad \forall i$ (2.15)

$$\sum_{j \in N_i} X_j = P \tag{2.16}$$

$$X_j, Z_i \in \{0,1\} \quad \forall i, \forall j \tag{2.17}$$

Jia et al. [44] proposed a model and solution approaches for determining the facility locations of medical supplies in response to large-scale emergencies. The problem was formulated as a maximal covering problem with multiple facility quality-of-coverage and quantity-of-coverage requirements. The objective was to maximize demand by ensuring a sufficient quantity of facilities at the stated quality level. A genetic algorithm, a located-allocated heuristic, and a Lagrangian relaxation heuristic were then developed to solve the problem. Murali et al. [45] developed a facility location problem to determine the points in a large city at which medication should be distributed in times of epidemic. Variations in the maximal covering problem were used to maximize the number of people receiving medication. The proposed model selected opened facilities and supplies, with demand being assigned to each location. Santos et al. [46] proposed a maximal covering problem with Lagrange optimization to optimize the number of strategic locations by relaxing constraints to obtain optimal demand coverage for each facility location. The objective was to optimize the number of demand points covered by the optimal number of facility locations. The problem was solved using a locate-allocate heuristic and a large-scale hypothetical anthrax attack emergency in Los Angeles County was used as a demonstration case study. Abounacer et al. [33] proposed a maximal covering problem with one of the objectives being to minimize the number of uncovered demands. Chanta and Sangsawang [47] studied an optimization model to find appropriate locations for temporary shelters in flood disasters, in which a bi-objective programming model was formulated to minimize total distance and maximize the number of people covered in the affected zones.

3. Minimax facility location problem

The minimax facility location problem, also known as the "P-center" problem, attempts to minimize the worst system performance within P facilities. The P-center focuses on a demand point being served by the nearest facility and how all demand points can be covered. The P-center problem can be applied to emergency humanitarian logistics' facility location planning for hospitals, fire stations, and other public facilities. The formulation for this problem is as follows [27]:

Decision variables (addition):

D the maximum distance between a selected location and a demand point

Minimize D (18)

Subject to $\sum_{j} X_j = P$ (19)

$$\sum_{j} Y_{ij} = 1 \qquad \forall i \qquad (20)$$

$$Y_{ij} \leq X_j \qquad \forall i,\ \forall j \qquad (21)$$

$$D \geq \sum_{j} d_{ij} Y_{ij} \qquad \forall i \qquad (22)$$

$$X_j, Y_{ij} \in \{0,1\} \qquad \forall i,\ \forall j \qquad (23)$$

The objective function is shown in equation (2.18), which seeks to minimize the maximum distance between a selected location and a demand point. Equations (2.19) – (2.21) are the same constraints as explained for equations (2.2), (2.3), and (2.6). Equation (2.22) forces D to be equal to the maximum distance, and equation (2.23) defines the binary variables in the model.

Talwar [48] studied the location of rescue helicopters in South Tyrol, Italy and utilized the P-center to optimize the locations for three rescue helicopters to serve the growing demand arising from tourist activity accidents. One of the models in this research sought to minimize the maximum or worst response times and heuristics were applied to test this model. Ye et al. [49] presented an emergency warehouse location problem model for a Chinese national emergency warehouse location problem using the P-center problem. The constraints population distribution, economic condition, transportation, and multi-coverage for some vital areas were included in the proposed model and a variable neighborhood search (VNS)-based heuristic algorithm was developed to solve the proposed model.

Normally, this problem is used as a risk guarantee for the longest distance between a demand point and a selected facility. The minimax facility location problem is quite different from the minisum facility location problem and the covering problem. The minisum facility location problem considers the locations of general facilities such as distribution centers and inventory, and the covering problem is similar to the minimax facility location problem as it concentrates on optimizing overall system performance within particular distance or time limits. However, the minimax facility location problem attempts to minimize the worst performance of the system by minimizing the longest distance or time between demand points and the selected facility within P facilities.

4. Obnoxious facility location problem

In contrast to sections 3.1.1–3.1.3, which focused on optimizing the distance between a demand point and a selected location (the nearer the better), the obnoxious facility location problem seeks to have demand points far from facilities but try to have it as close as possible such as chemical plants, nuclear reactors, garbage dumps, or wastewater treatment plants [36]. The objective function, therefore, is opposite to those outlined in sections 3.1.1–3.1.3, as follows:

- Maxisum facility location problems aim to select facility locations and maximize the total distance between a demand point and a selected location [50].
- Minimum covering problems aim to select facility locations and minimize the number of demand points covered [51].

- Maximin facility location problems aim to select facility locations and maximize the minimum distance between a demand point and a selected location [52].

In the field of emergency humanitarian logistics, this problem is one of opportunity for overcome this challenge. According to recovery stage in post disaster, some facility locations need to locate far from affected area but try to have it as close as possible such as debris (waste) or recycling site. The advantage of this problem can help to operate in post disaster for avoiding cause harm to the health of human beings and pollute or disgusted the environment after the disaster occurrence. A few obnoxious facility location problems have been proposed for emergency humanitarian logistics. Fetter and Rakes [53] developed a facility location model for locating temporary disposal and storage reduction (TDSR) in support of disaster debris cleanup operations. The proposed model aims to minimize the total fixed and variable costs of debris collection that consist of opening and closing cost of TDSRs, fixed cost of making RSR (reduction, separation, and recycling) technology available at the TDSR locations, operation cost of removing debris, variable cost of applying RSR technology, and the revenue received from selling recycled material. Hu and Sheu [54] proposed a revers logistics system for post-disaster debris management to minimize economic, risk-induced and psychological cost. The multi-objective linear programming is formulated to apply in Wenchuan Country of China. Others post-disaster debris operations are proposed by Lorca et al. [55], Pramudita et al. [56], and Sahin et al. [57].

2.3.2 Dynamic facility location problem

The first discussion examined deterministic emergency humanitarian logistics' facility location problems by deciding on a period of time (single-period model) in which the parameters were constant. However, generally, in real-world problems, the facility location problem is a decision that has long-term effects, so the parameters of the system such as the demand points, operating costs, distribution costs, and environmental factors may vary over time and facility additions can occur at different times (multi-period model). That is, not only where but also when to build a facility becomes a critical decision. Ballou [58] first proposed the dynamic facility location problem, after which Scott [13] proposed an efficient approach using dynamic programming.

There are two main factors in the dynamic facility location problem that affect the decision to select an appropriate location for the facility: cost and time. Cost is a trade-off between incurring expenditure to establish the new facility or modify a current facility, the opening and closing times for which are determined over the course of the planning time horizon [25]. This deterministic model can be reformulated as a dynamic deterministic model, in which there are T time periods ($t \in T$). The model formulation is as follows [59]:

Minimize
$$\sum_{t=1}^{T}\sum_{j=1}^{m_T} f_{tj}\left(x_t, y_t\right) + \sum_{t=2}^{T} r_t z_t \qquad (2.24)$$

Subject to
$$z_t = \begin{cases} 0 \text{ if } d_{t-1,t} = 0, \\ 1 \text{ else if } d_{t-1,t} > 0 \end{cases} \qquad (\text{for } t = 2, \ldots, T) \qquad (2.25)$$

In equation (2.24), there are m_t candidate destinations (candidate sites) in period t. The first term in equation (2.24) is the transport cost between a facility located at $\left(x_t, y_t\right)$ and destination j. Note that (x_t, y_t) is coordinates at period t. The second term in equation (2.24) is the relocation cost, r_t which defines the relocation cost in period t, with $d_{t-1,t}$ is the distance by which the facility is relocated in period t. Equation (2.25) is affected by this distance.

Moeini et al. [60] proposed a dynamic facility location model for locating and relocating a fleet of ambulances. The proposed model controlled the movements and locations of ambulances to provide better coverage of the demand points. The objective focused on minimizing both the demand points covered and the costs related to relocating the vehicle. Afshar and Haghani [61] presented a mathematical model that controlled the flow of several relief commodities from the source to the receiver by considering vehicle routing, pick-up or delivery schedules, the optimal location for several layers of temporary facilities, several capacity constraints for each facility, and the transportation system. Similarly, Khayal et al. [62] proposed a network flow model for the selection of temporary distribution facilities and the allocation of resources for emergency response planning. The objective function sought to minimize the logistics and deprivation costs of the relief distribution and consisted of the fixed costs, transportation and distribution costs, and the delay penalty costs. A case study was conducted using sample data from 15 cities in South Carolina, USA.

2.3.3 Stochastic facility location problem

For optimization under uncertainty, there have been two approaches, one of which is stochastic optimization, in which the uncertain parameters are allocated to a probability distribution. The stochastic facility location problem has been examined across a wide range of professional and academic fields, as it can respond well to real-world problems. The stochastic model can develop from deterministic model, in which the uncertain parameters can add in objective or constrain. For example, Salman and Yücel [16] formulated a stochastic integer programming model that determined the location of emergency response facilities (ERFs), with an objective to maximize the expected total demand within a predetermined distance parameter over all possible networks (equation (2.26)). The proposed model is as follows:

Indices and index sets (Addition);

S Set of periods; $s \in S$

Decision variables (Addition):

O_{ij}^{s} = 1 if demand point i is covered by a facility at location j in scenario s, and 0 otherwise.

E_{i}^{s} = 1 if demand point i is covered in scenario s, and 0 otherwise.

Input parameters (Addition):

$P(s)$ the occurrence probability of scenario s

g_{ij}^{s} = 1 if demand point i is covered by a facility at location j in scenario s, and 0 otherwise.

$$\text{Maximize} \quad \sum_i \sum_s P(s) w_i E_i^s \tag{2.26}$$

$$\text{Subject to} \quad \sum_j X_j \le P \tag{2.27}$$

$$E_i^s \le \sum_j O_{ij}^s \qquad \forall i, \forall s \tag{2.28}$$

$$O_{ij}^s \le g_{ij}^s X_j \qquad \forall i, \forall j, \forall s \tag{2.29}$$

$$O_{ij}^s, X_j, E_i^s \in \{0,1\} \qquad \forall i\ ,\ \forall j\ ,\ \forall s \tag{2.30}$$

Equation (2.27) allows at most P open ERFs. Equation (2.28) enforces that demand point i is covered in scenario s only if it is covered by at least one open facility. Equation (2.29) ensures that demand point i is covered by facility j in scenario s only if there is a surviving path shorter than the coverage distance limit between demand point i and facility j in scenario s. Equation (2.30) defines the binary variables in the model. The proposed model is a maximal covering problem. A Tabu search algorithm was proposed to solve Istanbul earthquake preparedness problems.

Similarly, Akgün et al. [7] studied DM risk for a demand point, so the proposed model sought to minimize the risks and select locations such that a reliable facility network to support the demand points could be constructed. The risk at a demand point was determined as the multiplication of the (probability of the) threat, the vulnerability of the demand point (the probability that it is not supported by the facilities), and the consequence (value or possible loss at the demand point due to threat). Balcik and Beamon [63] proposed maximal covering location model that integrates facility location problem and inventory decision problem for humanitarian relief chain under uncertainty scenarios. The proposed model considers multiple item types, captures budgetary constraints and capacity constraints. Others maximal covering problem is proposed by Murali et al. [45] that presented a maximal covering location problem with chance constraints to determine the points in a large city where medication should be distributed to the population, with the aim of maximizing the number of people serviced under both uncertain and limited time/resource conditions, and a hypothetical anthrax attack in Los Angeles County was solved using a locate-allocate heuristic. Duran [64] developed inventory location model which determined a set of typical demand instances and given a specified upfront inventory and finds the configuration of the supply network that minimize the average response time over all the demand instances. This article obtained the typical demand instances from historical data, and the supply network consists of the number and location of warehouses and the quantity and type of items held in inventory in each warehouse. Klibi et al. [65] studied the strategic problem of designing an emergency supply network to support disaster relief over a planning horizon. The proposed approach involved three phases: scenario generation, design generation, and design evaluation; a two-stage stochastic programming formulation was proposed using a sample average approximation method to solve the problem. The approach was assessed using a case study inspired from real-world data provided by the Northern Carolina emergency management division. Similarly, Rawls and Turnquist [66] proposed an emergency response planning tool that considers the location and quantities of various types of emergency supplies to be pre-positioned under uncertainty. The proposed mathematical model provides an emergency response pre-positioning strategy for hurricanes or other threats that determines uncertainty of demand and uncertainty regarding transportation network availability after an event. This study was tested with real case in the Gulf Coast area of the US by using the Lagrangian L-shaped method for solving the problem. Others stochastic programming in emergency humanitarian logistics' facility location problems were proposed by Manopiniwes and Irohara [67], Psaraftis et al. [68], Wilhelm and Srinivasa [69], Chang et al. [70], Rawls and Turnquist [71] and Mete and Zabinsky [72].

2.3.4 Robust facility location problem

The second of the two optimization approaches under uncertainty is robust optimization. For this problem, the probabilities are unknown, so the uncertain parameters are identified using discrete scenarios or continuous ranges. Robust optimization differs from stochastic optimization and sensitivity analysis in that robust optimization includes slack in the solution [73]. A few papers have addressed uncertainty parameters in the objective function, which is also known as a "penalty function," under varying scenarios [22]. Bertsimas et al. [74] addressed the general robust optimization as follows:

Minimize $$f_0(x) \tag{31}$$

Subject to $$f_i(x,u_i) <= 0, \ \forall u_i \in U_i, i = 1,...,m \tag{32}$$

$$x \in R^n, U_i \subseteq R^k$$

Where x is a vector for the decision variables, f_0 and f_i are as before, u_i indicates uncertain parameters (disturbance parameters), and U_i indicates are uncertainty sets, which, for this model, will always be closed. The objective of equation (2.31) is to determine minimum cost solutions x^* from all the feasible solutions for all realizations of the disturbances u_i within U_i. If the set of U_i is a singleton, the corresponding constraint has no uncertainty or certainty. Originally, this problem offered some measure of feasibility protection for optimization problems containing parameters that were not exactly known. There have been many formulas developed to tackle this challenge such as the extended Bertsimas-Sim (delta) Formulation and the extended chance constrained formula. For more detail, see Bertsimas et al. [74] for a review of the theory and applications of robust optimization.

Mulvey et al. [75] first proposed robust optimization, and since that time, it has been seen as an effective approach for the optimal design and management of supply chains operating in uncertain environments. Robust optimization has been used across many professional or academic fields, but its use in emergency humanitarian logistics is not widespread. Paul and Hariharan [76] proposed stockpile location and allocation planning for effective disaster mitigation, within which robust optimization and scenario planning were conducted to determine the final solution. Bozorgi-Amiri et al. [77] presented a multi-objective robust stochastic programming approach for disaster relief logistics under uncertainty that focused on demand, supplies, and the cost of procurement and transportation. The proposed model sought to locate the appropriate node for opening relief distribution centers so that the objective function minimized total cost and maximized demand coverage in the affected zone. Jabbarzadeh et al. [19] proposed a robust network design model for the supply of blood during and after disasters. The proposed model aimed to determine supply chain design decisions under a set of scenarios. The objective of the proposed model was to minimize the total supply chain costs for locating permanent facilities and moving temporary facilities, operational costs, inventory costs, and blood transportation costs. To transform the nonlinear model to an LP model, it was based on Mulvey et al. [75] and Yu and Li [78]. Similarly, Das and Hanaoka [79] presented robust network design with supply and demand uncertainties in humanitarian logistics that aims to minimize total cost of the network as well as the variance of total cost. This proposed model attempts to seek the location of relief distribution center (RDC), inventory level in each RDC and distribution of relief in different locations and procurement of relief. Finally, a case study on the earthquake in Bangladesh was used for validation of the proposed model.

From the examination of the deterministic, stochastic, dynamic, and robust facility location problems, the objectives, constraints, and solution methods associated with the emergency humanitarian logistics' facility location problem optimization model were summarized (Table 2.1). As can be seen, most of the identified objectives consist of risk, covered/uncovered demand, satisfied/unsatisfied demand, the number of selected facilities, evacuation time, transport time, transport distance, transport cost, the fixed cost at the selected facility, operating costs at the selected facility, and the number of demand points. Weight was also commonly applied to the objective function. Several constraints were added to facility selection such as facility capacity requirements and bounds. Constraints can be applied to other problems such as traffic assignment [17], commodity flows [33], and inventory [65]. For optimum solutions, exact algorithms have been commonly used. However, for large-scale data, exact algorithms can take a long time to solve, so advanced algorithms such as genetic algorithms [14], Tabu searches [16], clustering algorithms [76], and locate-allocate heuristics [44] are essential. For simplification, many techniques have been proposed to modify the models, especially for the stochastic and robust optimization models, such as the epsilon-constraint method and the sample average approximation method. Problem type, data modelling type, and facility location type are shown in Table 2.2, which presents a classification of the facility location problems and models identified from previous research. Most facility location problems were found to be minisum, set covering, miximal covering, and minimax facility location problems. Obnoxious facility location problems were the least proposed problems. As the deterministic model is the basis for the stochastic, dynamic, and robust facility location models, it has been used extensively in more complex facility location stochastic models such as Akgün et al. [7], Verma and Gaukler [12], and Salman and Yücel [16]. Dynamic and robust facility location problem models are not as widely spread as expected, and most tend to focus on shelters, distribution centers, warehouses, and medical centers. Some research has studied sub-facilities such as temporary distribution centers [61,62] and temporary shelters [80].

2.4 Application and case studies

Facility location problems have been applied to a wide range of problems such as evacuation, vehicle movements, transportation routes, relief distribution logistics, stock pre-positioning, casualty transportation, resource allocation, commodity flows, traffic control, and warehouse locations. Abounacer et al. [33] studied a facility location problem with a transportation problem for disaster response. Afshar and Haghani [61] proposed a mathematical model that integrated a relief commodity flow problem, a facility location problem, a vehicle routing problem, and a transportation problem. Bayram et al. [17] developed a model that optimally located shelters and assigned evacuees to the nearest shelter site.

Similarly, Kongsomsaksakul et al. [14] proposed a shelter location-allocation model for flood evacuation planning. The proposed model was formulated from a facility location problem and a CDA problem. Khayal et al. [62] presented a network flow model for dynamic selection of temporary distribution facilities and resource allocation for emergency response planning, in which a facility location problem, an allocation problem, a community flow problem, and a supply assignment problem were included in the formulation model. Feng and Wen [81] proposed a model that was formulated as a multi-commodity, two-model network flow problem (private vehicle flow and emergency vehicle) based on a bilevel programming problem and network optimization theory. Moeini et al. [60] proposed a dynamic location model for the locating and relocating of a fleet of ambulances. Kilci et al. [80] proposed MILP to select the location of a temporary shelter site, in which a facility location problem, an assignment problem, and a modified pairwise analysis were included. Following on from previous research, some case study, they can generate by exact algorithm because they can formulate real case by using a few variables and a few parameters. Moreover, some models, they used some technique to reduce the number of variable, parameter, and constraints such as Das and Hanaoka [[79, Irohara et al. [[36, and Bozorgi-Amiri et al. [.[77At the present, there are many advance software companies can overcome this challenge in which it can solve exact algorithm efficiency. However, heuristic algorithm is still necessary for solving large problem.

Emergency humanitarian logistics' facility location problem structures depend on the research goals. The most prevalent disaster investigations were found to be earthquakes, hurricanes, floods, dam inundations, and epidemics, and some papers proposed optimization models for general disaster scenarios. Numerical examples and real case studies were developed and illustrated to validate the mathematical models shown in Table 2.3.

2.5 Future research direction

In future research, facility location problems could be applied to many techniques such as decision making and simulation. To further the already valuable work, optimization models could also be used for dynamic or robust emergency humanitarian logistics' facility location models, which would allow for the incorporation of uncertain time periods, uncertain environments, facility location risks, the possibility of facility locations, uncertain demand, disruption events, different fluctuation patterns, and facility expansion.

The relationship between facility location types and disaster stages is shown in Figure 2.1. Disasters can be divided into the pre-disaster (mitigation and preparation) and post-disaster (response and recovery) stages. In the mitigation stage, future research could seek to treat hazards by relocating inhabitants farther from the risk area (arc (1)). As safety area planning is a long-term plan, dynamic and robust models could be adapted into mathematical models. In the preparation stage, research could investigate optimum planning and preparation for facility locations such as warehouses, shelters, permanent distribution centers, and permanent medical centers so as to increase the chances of survival and minimize financial and other losses.

Stochastic, dynamic, and robust facility planning models can be used to respond to real situations. For example, as distribution warehouses should be located near disaster sites but still place in safety area because they are the reception points for commodities and donations (domestic and international), suppliers, and NGOs, research could focus on when to transfer goods. Ye et al. [49] and Paul and Hariharan [76] developed a deterministic and robust model for emergency humanitarian logistic warehouses, but did not include a stochastic or dynamic model (arc (2)). For the response stage, emergency decision makers will have major role in this stage for managing available resources while the disaster is still progress that call this part as "Disaster in progress". This part, emergency decision makers are included but they just decide emergency decision when unexpected case or emergency case occurred. The most important considerations are shelters and medical centers that can respond to demand and ensure the wounded are transferred to medical centers. When permanent medical centers are located in the risk areas, the medical center needs to be able to evacuate patients to shelters as quickly as possible. Therefore, permanent medical centers should be located in safe areas, so further research could examine where to locate or relocate permanent medical centers. Immediately following the disaster, temporary shelters need to be rapidly identified, so emergency decision makers need to be able to identify suitable evacuation shelters as quickly as possible (arc (3)) [85-88]. Finally, in the recovery stage, research could investigate optimum locations for temporary distribution centers (sub-distribution centers) to ensure efficient commodity distribution, and also to determine the optimum placement of temporary medical centers to ensure that the wounded are treated rapidly. Dynamic temporary distribution center and medical center selection methods have been proposed, but none have included robust models. In addition, obnoxious facility location problems have not been widely employed in DM research, so while optimum facility locations as close as possible to the disaster areas have been investigated, considerations regarding facilities far from potential epidemic zones, such as centers for disease control and prevention (an epidemic may occur following a disaster) and garbage dumps for debris removal have not been fully studied (arc (4)). The relationships in this stage need to be further investigated as warehouses send commodities (food, medicine, clothes, etc.) to shelters and medical centers (medicines, medical equipment). Likewise, when an epidemic breaks out, both permanent and temporary medical centers send patients with illnesses or infections to centers for disease control and prevention.

Facility location problems can be supported or developed to combine aspects such as routing problems, evacuation problems, relief distribution problems, casualty transportation problems, inventory problems, resource allocation problems, traffic control problems, debris management problems, and community flow problems as elucidated in Zheng et al. [25]. In some situations, two disasters may occur, such as an earthquake followed by a tsunami. Therefore, more research is needed that considers multi-disaster scenarios. Moreover, integrated disaster stage management is also important for decision making in emergency humanitarian logistics' facility location problems. Normally, the researchers always focus on each stage and a few researches concentrate on integration disaster stage management, so integrated disaster stage management is a major gap that should be considered.

The objective function model could also be designed differently to create a single-objective or multi-objective model that could be single level or bilevel. Most objectives have focused on minimum time, minimum cost, minimum distance, minimum number of located facilities, and coverage by a maximum number of demand points. New objective functions could be developed by integrating the facility location problem with the other above-mentioned problems. Further, new objectives focused on environmental effect, reliability, risk, and ease of access could be developed. Constraints could also be added, such as an assessment of evacuee behavior (demand) and age of population (old age and childhood). For more realistic, the researchers should determine the uncertainty factors such as demand, supply and time. Moreover, quantitative and qualitative measurements could be added to the parameters so as to include quality measurements in facility location problems such as availability, accessibility, functional ability and risk. According to informed judgement of experts, it is one element that we should emphasize and bring to apply in mathematical model. However, the key question is not only "How can we optimize the facility location in emergency humanitarian logistic problems" but also "How can we seek the suitable facility location in emergency humanitarian logistic problems that we can commandeer and use" as well.

Current emergency humanitarian logistics' optimization models have some limitations due to the large-scale data, so it can be complex to calculate and finding the optimum can take an excessive amount of time and computing power. Therefore, the development of advanced algorithms that can be applied to emergency humanitarian logistics is necessary to add to the present stable of genetic algorithms, tabu searches, locate-allocate heuristics, Lagrangian relaxation heuristics, particle swarm optimization, ant colony optimization, biogeography-based optimization, artificial immune systems, and hybrid algorithms. See Zheng et al. [25] for a review of the research advances in evolutionary algorithms (EAs) applied to disaster relief operations.

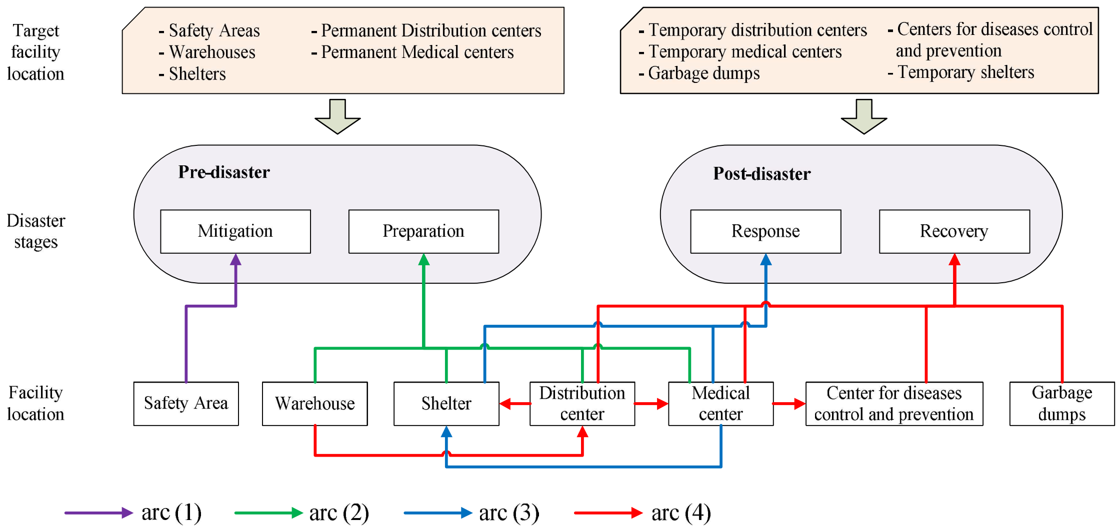


Figure 2.1 Relationship model between disaster stages and facility location types.

2.6 Conclusions

This chapter reviewed optimization models for emergency humanitarian logistics' facility location problems. Four main models were investigated: deterministic, stochastic, dynamic, and robust. The deterministic facility location problem addressed facility location problems for minisum problems, covering problems, minimax problems, and obnoxious problems. This review attempted to survey the objectives, conditions, case studies, applications, disaster types, facility location types, solution methods, and emergency humanitarian logistics' facility location problem categories. The literature's main objective was found to be focused on responsiveness, risk, and cost-efficiency. In emergency humanitarian logistics problems, responsiveness and risk are the major criteria, with most models aiming to minimize response time, evacuation time and/or distance, transportation costs (distance and time), the number of open facilities, facility fixed costs or operating costs, uncovered demand, unsatisfied demand, and risk, along with maximizing the demand points covered. Depending on the problem type, the literature showed that the problem types could be merged with other problems and that the facility location problem could be applied along with other techniques such as decision theory, queuing theory, and fuzzy methods. Owing to the prevalence of earthquakes, hurricanes, floods, and epidemics in the world, these were the main focus of emergency humanitarian logistics research. An exact solution was found to be one efficiency technique, but advanced algorithms were found to be most effective for large-scale problems. Finally, research gaps and future research were identified as assisting in developing future disaster operations. This review has highlighted the extensive range of emergency humanitarian logistics' facility location optimization models that have been developed since the 1950s.

Table 2.1 Objectives, constraints, and solution methods for emergency humanitarian logistics' facility location problem optimization models

Authors	Objective	Constraints: Capacity	Constraints: Requirements and bounds	Constraints: Other	Solution method
Abounacer et al. [33]	Transportation distance, the number of agent need to operate the opened HADCs, Uncovered demand	Facility, vehicle, link	Number of agent, number of trip performed (Vehicle), Daily work time for a vehicle, time limit	Transportation problem	Epsilon-constraint method, Exact Pareto front
Afshar and Haghani [61]	Unsatisfied demand	Facility, vehicle, Supply	Number of facility	Commodity flow, vehicle flow, transportation network design, linkage between vehicle and commodity	Exact algorithm
Akgün et al. [7]	Risk	-	Number of facility	-	Exact algorithm
Aksen and Aras [42]	Cost incurred before and after the interdiction attempt	Facility	Number of facility	-	Tabu search, Sequential solution method
Balcik and Beamon [63]	Total expected demand covered by the established distribution centers	Facility	Budget	Inventory problem	Exact algorithm
Barzinpour and Esmaeili [34]	Cumulative coverage of population, setup costs, transportation costs, equipment holding costs, shortage costs	Facility, transportation	-	Demand and supply	Exact algorithm (Goal programming)
Bayram et al. [17]	Evacuation time	Facility	Number of facility	Traffic assignment, balance flow, evacuation management	Second order cone programming techniques
Bozorgi-Amiri et al. [77]	The expected value and the variance of the total cost of the relief chain, satisfaction levels, shortages in the affected areas	Facility	-	Commodity flow, inventory	Exact algorithm (Lingo)
Chang et al. [70]	Transportation, facility opening, equipment rental, penalties, shipping distance of rescue equipment	Facility	-	Prioritized facility allocation	Sample average approximation
Chanta and Sangsawang [47]	Number of demand zones, Weight distance	Facility	Number of facility, distance limit	-	Epsilon-constraint approach, Exact algorithm
Chen et al. [84]	Distance	Facility	Number of assignment	Financial problem	Exact algorithm
Dar and Hanaoka [79]	Cumulative cost of pre- and post-disaster circumstances	Facility	Delivery capacity of supplier	-	Exact algorithm
Dekle et al. [38]	Facilities for each area with a given distance	-	Identify the location of the facility for each area	-	Pick-the-Farthest (PTF) Algorithm
Dessouky et al. [82]	Demand-weighted distance	Facility	Number of facility, distance limit	-	Exact algorithm
Duran et al [64]	Average response time	Facility	Number of facility, total inventory allowed	Inventory problem	Exact algorithm

Table 2.1 (Continues)

Authors	Objective	Constraints			Solution method
		Capacity	Requirements and bounds	Other	
Fetter and Rakes [53]	Fixed cost and variable cost of facility, making technology, operation, transportation, and revenue	Facility	Number of facility, the ability to characterize the debris from specific regions	-	Exact algorithm
Hale and Moberg [40]	Number of opened felicities	Facility	Minimum and maximum distance	-	Exact algorithm
Hong et al. [32]	Total logistic cost	-	Distance between warehouse and facility, number of facility, demand	-	Exact algorithm
Horner and Downs [30]	Cost of distributing relief goods	Facility	Number of facilities,	Demand fulfilment constraint	Exact algorithm
Hu et al. [41]	Cost of opening, travel evacuation distance	Facility	-	-	Genetic algorithm
Irohara et al. [36]	Costs of establishing the centers, cost of maintaining the pre-positioned inventories, the recovery costs post-disaster	Facility	Distance, number of evacuation centers	assignment of communities	Dual Ascent Solution
Jabbarzadeh et al. [19]	Fixed cost and variable cost of facility, operational cost, transportation cost, inventory cost	Facility (permanent and temporary)	The number of blood supply of donor group, storage capacity	-	Exact algorithm (Branch and bound: Lingo)
Jia et al. [44]	Covered demand	Facility	Number of facility	Quality level	Genetic algorithm, Locate-allocate heuristic, Lagrangean relaxation heuristic, Exact algorithm
Kedchaikulrat and Lohatepanont [83]	Cost structure and AHP score	Facility, vehicle	Size of the facility	-	Exact algorithm (Pareto dominance)
Khayal et al. [62]	Fixed cost, transportation cost of resource allocation,distribution cost, delay penalty cost	Facility, supply	-	Commodity flow, supply assignment, resource transfer, demand satisfaction	Exact algorithm
Kilci et al. [80]	Weight of operating candidate shelter	Facility	-	Pairwise utilization difference	Exact algorithm
Klibi et al. [65]	Transportation and procurement cost, Penalty associated to satisfying point of distribution demands	Facility, quantities of items	Budget, vendor supply quantities	Inventory level, risk level	Two-stage stochastic programming, Sample average approximation method, Monte-Carlo procedure, multi-criteria decision-making method
Kongsomsaksakul et al. [14]	Evacuation time	Facility, link	Link	Combined distribution, assignment problem	Genetic algorithm
Lin et al. [31]	Shortage penalty cost, delay delivery penalty cost, shipping cost, unfairness of service cost	Facility	Number of depots, trucks, travel time, delivery items quantity	-	Two-phase heuristic approach
Manopiniwes and Irohara [67]	Cost of opening, shipping cost, response time	Facility, Vehicle	Number of vehicles, Number of distribution centers, available response time	-	Exact algorithm (Goal Programming)

Table 2.1 (Continues)

Authors	Objective	Constraints			Solution method
		Capacity	Requirements and bounds	Other	
McCall [29]	Victim nautical miles, shortage)	Facility	Budget, delivery limit, the number of stockpile, the number of community	Unsatisfied demands	Exact algorithm
Mete and Zabinsky [72]	Warehouse operation, transportation time	Vehicle	Inventory shortage upper bound threshold	-	Exact algorithm
Moeini et al. [60]	Cost of Relocation of the vehicle, Covered demand	-	Number of ambulances, time	Relocation problem	Exact algorithm
Murali et al. [45]	Number of demand points	Facility	Number of facility, supply available during emergency	-	Locate-allocate heuristic
Paul and Hariharan [76]	Fatality cost, the cost of maintaining a stockpile	Facility	Budget	Senility, type of medical condition, unique nature of each type of disaster	Disaster event simulation-HAZUS-MH, Clustering Algorithm, Patient grouping algorithm, Exact algorithm
Psaraftis et al. [68]	Facility opening, stock acquisition, transportation, operations, unmet demand, delay	-	-	-	Exact algorithm
Ransikarbum and Mason [35]	Fairness/equity, unmet demand, network cost	Facility, road	Number of disrupted nodes and disrupted arcs, Budget	flow conservation	Exact algorithm (Goal Programming)
Rawls and Tumquist [71]	Costs of commodity acquisition, stocking decision, transportation, shortage, holding	Facility, link	Demand, number of facilities, inventory level	Resource allocation	Exact algorithm
Rawls and Turnquist [66]	Facility opening, transportation, unmet demand, holding	Facility, link	Number of facility	-	Lagrangian L-shaped method
Salman and Yücel [16]	Covered demand	-	Number of facility	All-pairs shortest path problem	Tabu search
Santos et al. [46]	Number of demand points	Facility	Number of facility, distance limit	-	Exact algorithm
Talwar [48]	Weight distance, Un-weight distance	Facility	Number of facility	-	Weiszfeld algorithm, Two-point and three-point search heuristics
Verma and Gaukler [12]	Transportation cost	Facility	Number of facility	Supplier	Exact algorithm, Modified L-shaped, Sample average approximation method, Master problem heuristic
Wilhelm and Srinivasa [69]	Facility opening and expansion, stock acquisition, operations	Facility	Time-phased cleanup requirement	-	Heuristics based on linear programming
Ye et al. [49]	Number of warehouses	-	Number of warehouses, distance limit	-	Variable neighborhood search, Exact algorithm

Table 2.2 Problem types, data modelling types, and facility location types for emergency humanitarian logistics' facility location problems

Author	Classification of facility location problems					Classification of data modelling				Facility location type
	Minisum	Set covering	Maximal covering	Minimax	Obnoxious	Deterministic	Stochastic	Dynamic	Robust	
Abounacer et al. [33]	×	×	×			×				Distribution centers (HADC)
Afshar and Haghani [61]	×							×		Temporary distribution centers
Akgün et al. [7]				×			×			Pre-positioning
Aksen and Aras [42]		×				×				Shelters
Balcik and Beamon [63]		×					×			Distribution centers
Barzinpour and Esmaeili [34]	×	×	×			×				Distribution centers
Bayram et al. [17]	×					×				Shelters
Bozorgi-Amiri et al. [77]	×						×		×	Relief distribution centers
Chang et al. [70]	×						×			Rescue resource storehouses
Chanta and Sangsawang [47]	×			×		×				Shelter
Chen et al. [84]	×					×				Shelter
Dar and Hanaoka [79]	×								×	Relief distribution centers
Dekle et al. [38]		×				×				Disaster recovery centers
Dessouky et al. [82]	×					×				Warehouse (Medical supplies)
Duran et al [64]	×						×			Warehouse
Feng and Wen [81]	×					×				Shelter
Fetter and Rakes [53]					×	×				Debris removal site
Hale and Moberg [40]		×				×				Storage facilities
Hong et al. [32]	×					×			×	Distribution warehouses and break of bulk points
Horner and Downs [30]	×					×				Distribution centers
Hu et al. [41]	×	×				×				Shelters
Irohara et al. [36]	×					×				Evacuation centers
Jabbarzadeh et al. [19]	×	×					×		×	Blood facilities, blood centers and blood donors
Jia et al. [44]			×			×				Medical supply distribution centers
Kedchaikulrat and Lohatepanont [83]	×					×				Warehouses
Khayal et al. [62]	×	×						×		Temporary Distribution centers
Kilci et al. [80]		×				×				Temporary shelters
Klibi et al. [65]	×						×			Distribution centers
Kongsomsaksakul et al. [14]	×					×				Shelters
Lin et al. [31]	×					×				Temporary depots
Manopiniwes and Irohara [67]	×						×			Relief distribution centers
Marcelin et al. [18]	×					×				Distribution facilities
McCall [29]	×					×				Stockpiles
Mete and Zabinsky [72]	×						×			Warehouses
Moeini et al. [60]			×					×		Ambulances
Murali et al. [45]			×			×	×			Point of disbursement
Paul and Hariharan [76]		×		×					×	Warehouse
Psaraftis et al. [68]	×						×			Equipment stockpiling facilities
Ransikarbum and Mason [35]	×					×				Relief warehouse
Rawls and Tumquist [71]	×							×		Storage facilities
Rawls and Turnquist [66]	×						×			Pre-positioning of supplies
Salman and Yücel [16]			×				×			Shelters
Santos et al. [46]			×			×				Shelters
Talwar [48]	×			×		×				Location of rescue helicopters
Verma and Gaukler [12]	×					×	×			Disaster response facilities and population centers
Wilhelm and Srinivasa [69]	×						×			Storage locations
Ye et al. [49]				×		×				Warehouses

Table 2.3 Disaster types and case studies for emergency humanitarian logistics' facility location problems

Authors	Disaster type	Case study
Abounacer et al. [33]	General	Numerical experiments
Afshar and Haghani [61]	General	Numerical experiments
Akgün et al. [7]	Earthquakes	Turkey
Aksen and Aras [42]	General	Numerical experiments
Balcik and Beamon [63]	Earthquake	National Geophysical Data Center
Barzinpour and Esmaeili [34]	Earthquake	Tehran
Bayram et al. [17]	General	Transportation network test problem, OR library, Istanbul road network
Bozorgi-Amiri et al. [77]	Earthquakes	Iran
Chang et al. [70]	Flood	Taipei City
Chanta and Sangsawang [47]	Flood	Bangkruai, Thailand
Chen et al. [84]	Earthquake	Beijing. China
Dar and Hanaoka [79]	Earthquake	Bangladesh
Dekle et al. [38]	General	Florida county
Dessouky et al. [82]	Epidemic	Anthrax disaster, Los Angeles
Duran et al. [64]	General	CARE International
Feng and Wen [81]	Earthquakes	Taiwan
Fetter and Rakes [53]	Hurricane	Chesapeake
Hale and Moberg [40]	General	Seven city example in the northeast
Hong et al. [32]	General	South Carolina
Horner and Downs [30]	General	Leon County, Florida
Hu et al. [41]	Earthquake	Chaoyang District of Beijing
Irohara et al. [36]	Hurricane	southeast USA
Jabbarzadeh et al. [19]	Earthquakes	Iran (IBTO)
Jia et al. [44]	Epidemic	Anthrax disaster, Los Angeles
Kedchaikulrat and Lohatepanont [83]	General	Thai Red Cross
Khayal et al. [62]	General	South Carolina, USA
Kilci et al. [80]	Earthquakes	Kartal, Istanbul, Turkey
Klibi et al. [65]	General	North Carolina
Kongsomsaksakul et al. [14]	Inundation of dam and reservoir	Longan network in Utah
Lin et al. [31]	Earthquake	Angeles County
Manopiniwes and Irohara [67]	Flood	Chiang Mai, Thailand
Marcelin et al. [18]	Hurricane	Leon country, Florida
McCall [29]	General	Australia
Mete and Zabinsky [72]	Earthquake	Seattle
Moeini et al. [60]	General	Val-de-Marene, France
Murali et al. [45]	Epidemic	Anthrax attack, Angeles
Paul and Hariharan [76]	Earthquakes, Hurricane	Northridge, Kartina
Psaraftis et al. [68]	Oil spills	New England
Ransikarbum and Mason [35]	Hurricane	South Carolina
Rawls and Tumquist [71]	Hurricane	North Carolina
Rawls and Turnquist [66]	Hurricane	Gulf Coast area of the US
Salman and Yücel [16]	Earthquakes	Istanbul
Santos et al. [46]	Flood	Marikina City, Philippines
Talwar [48]	General	South Tyrol, Northern Italy
Verma and Gaukler [12]	Earthquakes	California
Wilhelm and Srinivasa [69]	Oil spills	Galveston Bay Area
Ye et al. [49]	General	China

3.8 References

[1] Guha-Sapir, D., P. Hoyois, & R. Below. 2015. Annual Disaster Statistical Review 2014, The Numbers and Trends. Brussels, CRED.

[2] Özdamar, L., & Ertem, M. A. (2015). Models, solutions and enabling technologies in humanitarian logistics. European Journal of Operational Research, 244(1), 55-65.

[3] World Health Organization. 2007., Risk reduction and emergency preparedness: WHO six-year strategy for the health sector and community capacity development. Available from: http://www.who.int/hac/techguidance/preparedness/emergency_preparedness_eng.pdf. Accessed 11 November 2015.

[4] Lehtveer, M., & Hedenus, F. (2015). Nuclear power as a climate mitigation strategy–technology and proliferation risk. Journal of Risk Research. 18(3), 273–290.

[5] Lidskog, R., & Sjödin, D. (2015). Risk governance through professional expertise. Forestry consultants' handling of uncertainties after a storm disaster. Journal of Risk Research. 1–16.

[6] Xu, J., Wang, Z., Shen, F., Ouyang, C., & Tu, Y. (2016). Natural disasters and social conflict: A systematic literature review. International journal of disaster risk reduction, 17, 38-48.

[7] Akgün, İ., Gümüşbuğa, F., & Tansel, B. (2015). Risk based facility location by using fault tree analysis in disaster management. Omega, 52, 168-179.

[8] Coppola, D. P. (2011), Introduction to international disaster management. Butterworth-Heinemann.

[9] Habib, M. S., Lee, Y. H., & Memon, M. S. (2016). Mathematical models in humanitarian supply chain management: A systematic literature review. Mathematical Problems in Engineering, 2016.

[10] Sauer, A. (2016). Humanitarian Supply Chain Performance Management: Development and Evaluation of a Comprehensive Performance Measurement Framework Based on the Balanced Scorecard. Doctoral dissertation, Munich Business School, German.

[11] Labib, A., & Read, M. (2015). A hybrid model for learning from failures: The Hurricane Katrina disaster. Expert Systems with Applications. 42(21), 7869–7881.

[12] Verma, A., & Gaukler, G. M. (2015). Pre-positioning disaster response facilities at safe locations: An evaluation of deterministic and stochastic modeling approaches. Computers & Operations Research. 62, 197–209.

[13] Scott, A. J. (1971). Dynamic location-allocation systems: some basic planning strategies. Environment and Planning. 3(1), 73–82.

[14] Kongsomsaksakul, S., Yang, C., & Chen, A. (2005). Shelter location-allocation model for flood evacuation planning. Journal of the Eastern Asia Society for Transportation Studies. 6, 4237–4252.

[15] Mete, H. O., & Zabinsky, Z. B. (2010). Stochastic optimization of medical supply location and distribution in disaster management. International Journal of Production Economics. 126(1), 76–84.

[16] Salman, F. S., & E. Yücel, (2015). Emergency facility location under random network damage: Insights from the Istanbul case. Computers & Operations Research. 62, 266–281.

[17] Bayram, V., Tansel, B. Ç., & Yaman, H. (2015). Compromising system and user interests in shelter location and evacuation planning. Transportation research part B: methodological. 72, 146–163.

[18] Marcelin, J. M., Horner, M. W., Ozguven, E. E., & Kocatepe, A. (2016). How does accessibility to post-disaster relief compare between the aging and the general population? A spatial network optimization analysis of hurricane relief facility locations. International journal of disaster risk reduction, 15, 61-72.

[19] Jabbarzadeh, A., Fahimnia, B., & Seuring, S. (2014). Dynamic supply chain network design for the supply of blood in disasters: a robust model with real world application. Transportation Research Part E: Logistics and Transportation Review, 70, 225-244.

[20] Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. European journal of operational research. 175(1), 475–493.

[21] Galindo, G., & Batta, R. (2013). Review of recent developments in OR/MS research in disaster operations management. European Journal of Operational Research. 230(2), 201–211.

[22] Caunhye, A. M., Nie, X., & Pokharel, S. (2012). Optimization models in emergency logistics: A literature review. Socio-Economic Planning Sciences. 46(1), 4–13.

[23] Safeer, M., Anbuudayasankar, S. P., Balkumar, K., & Ganesh, K. (2014). Analyzing transportation and distribution in emergency humanitarian logistics. Procedia Engineering, 97, 2248-2258.

[24] Anaya-Arenas, A. M., Renaud, J., & Ruiz, A. (2014). Relief distribution networks: a systematic review. Annals of Operations Research, 223(1), 53-79.

[25] Zheng, Y. J., Chen, S. Y., & Ling, H. F. (2015). Evolutionary optimization for disaster relief operations: a survey. Applied Soft Computing. 27, 553–566.

[26] Arabani, A. B., & Farahani, R. Z. (2012). Facility location dynamics: An overview of classifications and applications. Computers & Industrial Engineering. 62(1), 408–420.

[27] Hakimi, S. L. (1964). Optimum locations of switching centers and the absolute centers and medians of a graph. Operations research. 12(3), 450–459.

[28] Revelle, C. S., Eiselt, H. A., & Daskin, M. S. (2008). A bibliography for some fundamental problem categories in discrete location science. European Journal of Operational Research, 184(3), 817-848.

[29] McCall, V. M. (2006). Designing and prepositioning humanitarian assistance pack-up kits (HA PUKs) to support pacific fleet emergency relief operations. Doctoral dissertation, Monterey California, Naval Postgraduate School, California

[30] Horner, M. W., & Downs, J. A. (2010). Optimizing hurricane disaster relief goods distribution: model development and application with respect to planning strategies. Disasters. 34(3), 821–844.

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

[32] Hong, J. D., Xie, Y., & Jeong, K. Y. (2012). Development and evaluation of an integrated emergency response facility location model. Journal of Industrial Engineering and Management. 5(1), 4.

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

[34] Barzinpour, F., & Esmaeili, V. (2014). A multi-objective relief chain location distribution model for urban disaster management. The International Journal of Advanced Manufacturing Technology, 70(5-8), 1291–1302.

[35] Ransikarbum, K., & Mason, S. J. (2016). Multiple-objective analysis of integrated relief supply and network restoration in humanitarian logistics operations. International Journal of Production Research. 54(1), 49–68.
[36] Irohara, T., Kuo, Y. H., & Leung, J. M. (2013). From preparedness to recovery: a tri-level programming model for disaster relief planning. In International Conference on Computational Logistics (pp. 213-228). Springer Berlin Heidelberg.
[37] Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. Operations research, 19(6), 1363-1373.
[38] Dekle, J., Lavieri, M. S., Martin, E., Emir-Farinas, H., & Francis, R. L. (2005). A Florida county locates disaster recovery centers. Interfaces, 35(2), 133-139.
[39] Ablanedo-Rosas, J. H., Gao, H., Alidaee, B., & Teng, W. Y. (2009). Allocation of emergency and recovery centres in Hidalgo, Mexico. International Journal of Services Sciences, 2(2), 206-218.
[40] Hale, T., & Moberg, C. R. (2009). Improving supply chain disaster preparedness: A decision process for secure site location. International Journal of Physical Distribution & Logistics Management. 35(3), 195–207.
[41] Hu, F., Yang, S., & Xu, W. (2014). A non-dominated sorting genetic algorithm for the location and districting planning of earthquake shelters. International Journal of Geographical Information Science. 28(7), 1482-1501.
[42] Aksen, D., & Aras, N. (2012). A bilevel fixed charge location model for facilities under imminent attack. Computers & Operations Research. 39(7), 1364–1381.
[43] Church, R., & Velle, C. R. (1974). The maximal covering location problem. Papers in regional science. 32(1), 101–118.
[44] Jia, H., Ordóñez, F., & Dessouky, M. M. (2007). Solution approaches for facility location of medical supplies for large-scale emergencies. Computers & Industrial Engineering. 52(2), 257–276.
[45] Murali, P., Ordóñez, F., & 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.
[46] Santos, M. G., Meriño, M., Sore, N., & Quevedo, V. C. (2013). Flood Facility Location-Allocation in Marikina City Using MCLP with Lagrange. The 14th Asia Pacific Industrial Engineering and Management Systems Conference, Philippines, December 3–6.
[47] Chanta, S., & Sangsawang, O. (2012). Shelter-site selection during flood disaster. Lecture Notes in Management Science. 4, 282–288.
[48] Talwar, M. (2002). Location of rescue helicopters in South Tyrol. In proceeding of 37th Annual ORSNZ Conference, Auckland, New Zealand.
[49] Ye, F., Zhao, Q., Xi, M., & Dessouky, M. (2015). Chinese National Emergency Warehouse Location Research based on VNS Algorithm. Electronic Notes in Discrete Mathematics. 47, 61–68.
[50] Church, R. L., & Garfinkel, R. S. (1978). Locating an obnoxious facility on a network. Transportation science. 12(2), 107–118.
[51] Berman, O., Drezner, Z., & Wesolowsky, G. O. (1996). Minimum covering criterion for obnoxious facility location on a network. Networks. 28(1), 1–5.
[52] Drezner, Z., & Wesolowsky, G. O. (1980). A maximin location problem with maximum distance constraints. AIIE transactions. 12(3), 249–252.

[53] Fetter, G., & Rakes, T. (2012). Incorporating recycling into post-disaster debris disposal. Socio-Economic Planning Sciences. 46(1), 14–22.
[54] Hu, Z. H., & Sheu, J. B. (2013). Post-disaster debris reverse logistics management under psychological cost minimization. Transportation Research Part B: Methodological. 55, 118–141.
[55] Lorca, Á., Çelik, M., Ergun, Ö., & Keskinocak, P. (2015). A decision-support tool for post-disaster debris operations. Procedia Engineering, 107, 154-167.
[56] Pramudita, A., Taniguchi, E., & Qureshi, A. G. (2014). Location and routing problems of debris collection operation after disasters with realistic case study. Procedia-Social and Behavioral Sciences, 125, 445-458.
[57] Sahin, H., Kara, B. Y., & Karasan, O. E. (2016). Debris removal during disaster response: A case for Turkey. Socio-Economic Planning Sciences, 53, 49-59.
[58] Ballou, R. H. (1968). Dynamic warehouse location analysis. Journal of Marketing Research. 271–276.
[59] Wesolowsky, G. O. (1973). Dynamic facility location. Management Science. 19(11), 1241–1248.
[60] Moeini, M., Jemai, Z., & Sahin,E. (2015). Location and relocation problems in the context of the emergency medical service systems: a case study. Central European Journal of Operations Research. 23(3), 1–18.
[61] Afshar, A., & Haghani, A. (2012). Modeling integrated supply chain logistics in real-time large-scale disaster relief operations. Socio-Economic Planning Sciences. 46(4), 327–338.
[62] Khayal, D., Pradhananga, R., Pokharel, S., & Mutlu, F. (2015). A model for planning locations of temporary distribution facilities for emergency response. Socio-Economic Planning Sciences, 52, 22-30.
[63] Balcik, B., & Beamon, B. M. (2008). Facility location in humanitarian relief. International Journal of Logistics. 11(2), 101–121.
[64] Duran, S., Gutierrez, M. A., & Keskinocak,P. (2011). Pre-positioning of emergency items for CARE international. Interfaces. 41(3), 223–237.
[65] Klibi, W., Ichoua, S. & Martel, A. (2013). Prepositioning emergency supplies to support disaster relief: a stochastic programming approach. Faculté des sciences de l'administration, Université Laval
[66] Rawls, C. G., & Turnquist, M. A. (2010). Pre-positioning of emergency supplies for disaster response. Transportation research part B: Methodological. 44(4), 521–534.
[67] Manopiniwes, W., & Irohara, T. (2016). Stochastic optimisation model for integrated decisions on relief supply chains: preparedness for disaster response. International Journal of Production Research. 1–18.
[68] Psaraftis, H. N., Tharakan, G. G., & Ceder, A. (1986). Optimal response to oil spills: the strategic decision case. Operations Research, 34(2), 203-217.
[69] Wilhelm, W. E., & Srinivasa, A. V. (1996). A Strategic, Area-wide Contingency Planning Model for Oil Spill Cleanup Operations with Application Demonstrated to the Galveston Bay Area. Decision Sciences. 27(4), 767–799.
[70] Chang, M. S., Tseng, Y. L., & 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.

[71] Rawls, C. G., & 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.
[72] Mete, H. O., & Zabinsky, Z. B. (2010). Stochastic optimization of medical supply location and distribution in disaster management. International Journal of Production Economics. 126(1), 76–84.
[73] Marla, L. (2007). Robust optimization for network-based resource allocation problems under uncertainty. M.Sci diss. Massachusetts Institute of Technology.
[74] Bertsimas, D., Brown, D. B., & Caramanis, C. (2011). Theory and applications of robust optimization. SIAM review. 53(3), 464–501.
[75] Mulvey, J. M., R. J. Vanderbei, & Zenios, S. A. (1995). Robust optimization of large-scale systems. Operations research. 43(2), 264–281.
[76] Paul, J. A., & Hariharan, G. (2012). Location-allocation planning of stockpiles for effective disaster mitigation. Annals of operations research. 196(1), 469–490.
[77] Bozorgi-Amiri, A., Jabalameli, M. S., & Al-e-Hashem, S. M. (2013). A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty. OR spectrum. 35(4), 905–933.
[78] Yu, C. S., & Li, H. L. (2000). A robust optimization model for stochastic logistic problems. International Journal of Production Economics. 64(1), 385–397.
[79] Das, R., & HANAOKA, S. (2013). Robust network design with supply and demand uncertainties in humanitarian logistics. Journal of the Eastern Asia Society for Transportation Studies. 10(0), 954–969.
[80] Kilci, F., Kara, B. Y., & Bozkaya, B. (2015). Locating temporary shelter areas after an earthquake: A case for Turkey. European Journal of Operational Research. 243(1), 323–332.
[81] Feng, C. M., and Wen, C. C. (2005). A bi-level programming model for allocating private and emergency vehicle flows in seismic disaster areas. In Proceedings of the Eastern Asia Society for Transportation Studies. 5(5), 1408–1423.
[82] Dessouky, M., Ordonez, F., Jia, H., & Shen, Z. (2013). "Rapid Distribution of Medical Supplies." Patient Flow. Springer US, 385–410.
[83] Kedchaikulrat, L., & Lohatepanont, M. (2015). Multi-Objective Location Selection Model for Thai Red Cross's Relief Warehouses. In Proceedings of the Eastern Asia Society for Transportation Studies. 10.
[84] Chen, Z., Chen, X., Li, Q., & Chen, J. (2013). The temporal hierarchy of shelters: a hierarchical location model for earthquake-shelter planning. International Journal of Geographical Information Science, 27(8), 1612–1630.
[85] Boonmee, C., Takumi, A., & Mikiharu, A. (2017). A Bi-Criteria Optimization for Hierarchical Evacuation and Shelter Site Selection under Uncertainty of Flood Events. Journal of the Eastern Asia Society for Transportation Studies, In press.
[86] Boonmee, C., Takumi, A., & Mikiharu, A. (2017). Improving Evacuation Planning and Shelter Site Selection for Flood Disaster: Thai Flooding Case Study. Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management), Vol. 73(5), p. 253-267.
[87] Boonmee, C., Naotaka, I., Takumi, A., & Mikiharu, A. (2017). An Integrated Multi-Model Optimization and Fuzzy AHP for Shelter Site Selection and Evacuation Planning. Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management), Vol. 73(5), p. 225-240.

[88] Naotaka, I., Takumi, A., Boonmee, C., & Mikiharu, A. (2016). Built on The Local Disaster Prevention Education tool using Evacuation Drill Probe Data. Journal of Japan Society of Civil Engineers, Vol. 72(5), p. 331-339. (Japanese)

Chapter 3

An Integrated Multi-Model Optimization and Fuzzy AHP for Shelter Site Selection and Evacuation Planning

3.1 Introduction

Since the 1950s, both the number and magnitude of disasters have been continuously increasing, with the number of affected people has increased in proportion (about 235 million people per annum on average since the 1990s). Base on annual disaster statistical review 2014 [1], 324 natural disasters were recorded, with economic damages estimated to be US$ 99.2 billion. According to the international disaster database, Asia and America have been the continues most affected by natural disasters such as earthquakes, storms, floods, landslides, etc [2]. The World Health Organization (WHO) defines a 'disaster' as any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area [3]. Such events may include natural disasters and epidemics or man-made disruptions [4]. Because of the increasing severity of the disaster, research has paid more attention for the purpose of helping at-risk persons to avoid or recover from the effect of the disaster that known as "Disaster management" (DM). The DM activity consists of four stages: mitigation, preparation, response, and recovery [5].

During a disaster situation, people in an affected zone have to decide where to evacuate to safety. The shelter is a public safe place provided and organized by the government in order to support people in an affected area. Shelter site selection and evacuation planning are the most important function of DM. To find out the best planning, the modeling, optimization, decision making, and simulation are the major approach to overcome these challenges [6]. Since by deciding the best plan for shelter site and evacuation planning, local government can help at-risk persons to avoid or recover from the effect of the disaster. According to related existing papers, there are two problems that should be determined; (1) the existing papers normally focus on either qualitative measurement or qualitative measurement and propose only one standard model for shelter site selection and evacuation planning in which in some case, the model cannot apply to the real case problem and cannot respond to the perspective of decision makers. (2) To decide the best planning with relative to the perspective of decision-makers and the qualitative and quantitative criteria, this decision becomes complicated in the case of multiple conflicting criteria and imprecise parameters. Besides, the uncertainty and vagueness of expert's opinion are the prominent characteristics of the problem.

Therefore, this chapter aims to propose our conceptual model by using an optimization technique and Fuzzy Analytic Hierarchy Process (Fuzzy AHP) for selecting shelters and evacuation planning. The optimization technique is used to overcome the first problem, while the Fuzzy AHP is used to overcome the second problem. The highlight of this study not only present proposed several mathematical models under different constraints and model types, how to select an appropriate plan with relative to the perspective of decision-makers, but also present an integrated qualitative and quantitative measurement for considering DM plan as well.

The remainder of this study is organized as follows: Section 3.2 presents a review of related literature. Section 3.3 shows methodology of research. Section 3.4 addresses proposed mathematical models. A case study is given in section 3.5. Section 3.6 shows the computational results. Finally, the conclusion and future research are presented in section 3.7.

3.2 Literature review

Facility location problems and assignment problems are a basis for shelter site selection and evacuation planning. Facility location problems can be divided into four main parts that consist of minisum facility location problems, covering problems, minimax facility location problems, and obnoxious facility location problems [7]. There are many related papers dealing with sheltering and evacuation operations. Chanta and Sungsawang [8] proposed bi-objective optimization model to find appropriate temporary shelter sites. The objective of this study aims to maximize the number of victims that can be covered within a fixed distance and to minimize the total distance of all victims to their closest shelters. Santos et al. [9] presented flood facility location-allocation in Marikana city by using maximal covering location problems (MCLP) with Lagrange optimization model. This study attempt to select shelter by considering flood level constraint. In a related study, Anping [10] proposed two mathematical models that are variations of the maximum set covering problem for selecting the shelter site location after a disaster. Li and Jin [11] considered the stochastic nature of hurricanes and proposed this randomness by generating different scenarios and respective occurrence probabilities. Moreover, Dalal et al. [12] presented the problem same as Li and Jin [11] by using a clustering approach. Kilci et al. [13] proposed a Mixed Integer Linear Programming (MILP) for selecting the temporary shelter sites. Not only assigning each district to the closest open shelter area, providing the capacity of shelter areas, controlling the minimum utilization and pair-wise utilization difference of open shelter areas, but also making sure that each open shelter area has the main road connection and a health institution within a limited distance. Kongsomsaksakul et al. [14] studied optimal shelter location for flood evacuation planning, bi-level programming model was formulated. Another bi-level programming model was proposed by Feng and Wen [15] for managing the emergency vehicle and controlling the private vehicle flows in earthquake disaster. They consider a multi-community, two-model network flow problem base on the concept of bi-level programming and network optimization theory. Furthermore, the shelter location and evacuation planning were studied with respect to traffic management by Bayram et al. [16] The proposed model is Mix Integer Non-Linear Programming (MINLP) that optimally locates shelters and assigns evacuees to the nearest shelter sites by assigning them to shortest paths, shortest and nearest with a given degree of tolerance.

Not only mathematical model but also multiple criteria decision-making (MCDM) have been proposed to apply for shelter site selection and evacuation planning. Chu and Su [17] proposed the application of TOPSIS method in selecting fixed seismic shelter for evacuation in cities. This chapter proposed evaluation system that consists of 3 first-level indices and 9 second-level indices related to influential factors such as the risk of hazard, location & size and rescue facilities. Moreover, Bozorgi-Amiri and Asvadi [18] studied proposing a decision support system for prioritizing relief logistic center's locations (RLC) to facilitate providing emergency helps when natural disasters occur. This study focuses on availability, risk, technical, cost and coverage in locating relief logistic centers. The analytic hierarchy process (AHP), lexicographic goal programming (LGP) and two-step logarithmic goal programming (TLGP) are applied for prioritizing RLC's locations.

Base on comprehensive literature review, most reviewed papers propose only one standard model or one plan in which some case, the model cannot apply to the real case problem and response to the perspective of decision-makers or local government. Moreover, the related existing literature in this field is lacking an integrated quantitative measurement and qualitative measurement for evacuation planning and shelter site selection. As above-mention problems are scarce, we propose such a problem in our study. This chapter aims to propose the conceptual model for selecting shelter site and evacuation planning that considers both quantitative measurement and qualitative measurement simultaneously by integrating mathematical optimization technique and multiple criteria decision-making technique. Furthermore, the uncertainty and vagueness of expert's opinion are considered in this study as well. The detail of a conceptual model is described in next section.

3.3 Methodology

In this section, we address a conceptual model which separates in two phases: (1) mathematical optimization phase and (2) multiple criteria decision-making phase. The conceptual model is shown in Figure 3.1 and given detail as follows:

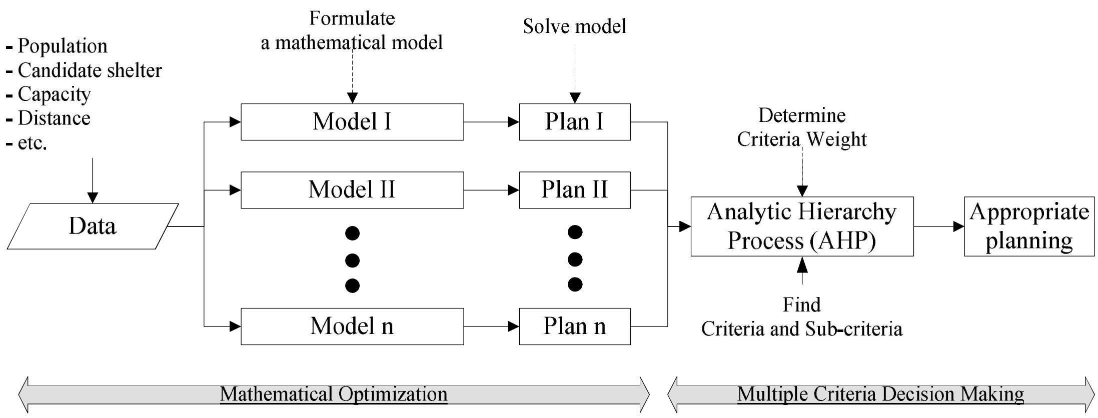


Figure 3.1 The conceptual model of the research

3.3.1 Mathematical optimization

This phase explains the method of optimization technique in which this section considers quantitative measurement. The several models or several plans are created in this phase for being the alternatives of evacuation planning. Firstly, the data of case study is collected and studied such as population in each community, the position of candidate shelters and communities, the distance between communities and candidate shelters, and the capacity in each candidate shelter. Then, the mathematical models are formulated under different constraints and model types (deterministic model, stochastic model, and robust model). Next, the mathematical models are coded and run in the optimized solver. Finally, the result of mathematical models is presented to decision makers for determining the appropriate model/plan in which the detail of methodology is described in section 3.2.

3.3.2 Multiple Criteria Decision Making (MCDM)

Multiple Criteria Decision Making (MCDM) is a decision management under attribute, objective, goal, and criteria. Fuzzy Analytic Hierarchy Process (Fuzzy AHP) is an approach in

MCAM for determining comparative judgments by decision makers. The proposed alternatives from mathematical models are evaluated for selecting the best plan. This phase focuses on qualitative and quantitative measurement for determining accessibility, availability, sustainability, total distance, and risk perspective. The typical Fuzzy AHP method consists of seven steps as follows:

Step 1: Define the problem and determine a goal, main criteria, and sub-criteria. The attributes are sought from some literature reviews and decision maker's brainstorming.

Step 2: Structure the decision hierarchy from top to lowest. The first level is target or goal of the research. The second level is main criteria. The third level is sub-criteria. Finally, the fourth level is alternatives in which the result of mathematical models is alternatives in this study.

Step 3: Construct a scale of numbers that indicate how many time more important or dominant on. A Linguistic term of Yasemin Claire Erensal et al. [19] is applied to use in this study that is shown in Table 1. A triangle fuzzy number, shown as $\tilde{A} = (a, b, c)$, is defined as following equation (3.1) and Table 3.1.

$$Triangle(x:a,b,c)=\begin{cases} 0 & x<a \\ (x-a)/(b-a) & a\le x\le b \\ (c-x)/(c-b) & b\le x\le c \\ 0 & x\ge c \end{cases} \tag{3.1}$$

Table 3.1 Linguistic variable and fuzzy scales

Linguistic term	Fuzzy number	Triangle fuzzy number
Equally important	$\tilde{1}$	(1,1,1)
Weakly important	$\tilde{3}$	(2,3,4)
Fairly important	$\tilde{5}$	(4,5,6)
Strongly important	$\tilde{7}$	(6,7,8)
Absolutely important	$\tilde{9}$	(9,9,9)
The intermittent values between two adjacent scales	$\tilde{2}$	(1,2,3)
	$\tilde{4}$	(3,4,5)
	$\tilde{6}$	(5,6,7)
	$\tilde{8}$	(7,8,9)

Step 4: Make a pairwise comparison in each attribute. According to the corresponding triangular fuzzy number of these linguistic terms, for example, if the decision maker mentions "Criterion 1 (A) is fairly important than Criterion 2 (B)", then it takes the fuzzy triangular scale as (4,5,6). On the other hand, the comparison of Criterion 2 (B) to Criterion 1 (A) will take the fuzzy triangular scale as (1/6,1/5,1/4). For more detail, see Junior et al. [20] for definition. The pairwise comparison matrix is showed as equation (3.2), where $\tilde{x}_{ij}^{r}$ indicates r^{th} decision maker's preference of i^{th} criterion over j^{th} criterion, via fuzzy triangular number.

$$\tilde{A}^r = \begin{bmatrix} \tilde{x}_{11}^r & \tilde{x}_{12}^r & \cdots & \tilde{x}_{1n}^r \\ \tilde{x}_{21}^n & \vdots & \cdots & \tilde{x}_{2n}^n \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{n1}^n & \tilde{x}_{n2}^n & \cdots & \tilde{x}_{nn}^r \end{bmatrix} \tag{3.2}$$

For more than one decision maker, the decision maker's preferences are calculated as in the equation (3.3). Then, it is proposed in equation (3.4).

$$\tilde{x}_{ij} = \frac{\sum_{r}^{R} \tilde{x}_{ij}^r}{R} \tag{3.3}$$

$$\tilde{A} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \cdots & \vdots \\ \tilde{x}_{n1} & \cdots & \tilde{x}_{nn} \end{bmatrix} \tag{3.4}$$

Step 5: According to Buckley [21], geometric mean method/eigenvector is proposed to calculate fuzzy comparison values of criterion as shown in equation (3.5). Next, the equation (3.6) is used for determining the relative fuzzy weight of each criterion. After that, the equation (3.6) is de-fuzzified by equation (3.7) which was proposed by Chang and Yang [22]. Finally, the equation (3.7) needs to be normalized by following equation (3.8).

$$\tilde{q}_i = \left(\prod_{j=1}^{n} \tilde{x}_{ij} \right)^{1/n}, i = 1, 2, \ldots, n \tag{3.5}$$

$$\tilde{w}_i = \tilde{q}_i \otimes (\tilde{q}_1 \oplus \tilde{q}_2 \oplus \ldots \oplus \tilde{q}_n)^{-1} = (aw_i, bw_i, cw_i) \tag{3.6}$$

$$M_i = \frac{aw_i + 4bw_i + cw_i}{6} \tag{3.7}$$

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{3.8}$$

Step 6: Calculate relative contribution weight. Consistency Ratio (CR) test is proposed to check the relative comparison data that calculates as equation (3.9). If the obtained CR is less than 0.1, the comparisons made will be acceptable. Consistency Index (CI) indicates the offset degree from consistency which is obtained as following equation (3.10).

$$CR = \frac{CI}{RI} \tag{3.9}$$

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{3.10}$$

Where n is the size of matrix of pairwise comparison, RI is random index which showed in Table 3.2, and λ_{max} is the largest value of the matrix that is calculated as equation (3.11)

$$\lambda_{\max} = \frac{\sum_{i=1}^{n} \frac{k_i}{r_i}}{n} \tag{3.11}$$

Table 3.2 Randomly generated consistency index for different sizes of matrix [23]

n	3	4	5	6	7	8	9	10
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Step 7: Find the normalized weight of both criteria and alternatives. Then by multiplying each alternative weight with related criteria, the score for each alternative is calculated. Finally, the result is found, the highest score is proposed to suggest to the decision makers for the appropriate plan in evacuation planning and shelter site selection.

3.4 Proposed mathematical model

The mathematical models are proposed for shelter site selection and evacuation planning. The objective in each model is to minimize travel distance between affected communities to candidate shelters. All mathematical models are formulated under different constraints and model types. Following the objective of this study, we aim to proposed several alternatives for selecting the best alternative in the perspective of decision-makers or local government. Therefore, four mathematical models are proposed for this case study that considers the assignment of communities to the nearby shelter sites, providing the capacity of shelter sites, the distance limit, the number of shelter sites limit, and the number of demand. Each proposed mathematical model presents the difference in attitude or viewpoint, solution, and character that depends on the considered parameters and model types. The first model formed the basis for the second, third and fourth model. Hence, this solution is a basic solution that all parameters being known and constant over time. To consider uncertain criteria, the second model is formulated in which this model focuses on the uncertain distance during the evacuation. The uncertain distance might occur during evacuation since the evacuee of each affected zone can go to the shelters with several routes. So, this is one of the criteria should be considered. Meanwhile, another of the important criteria should be determined is an uncertain situation of the expected population in which this can affect to shelter site selection and evacuation planning as well. So, the third model is formulated for supporting this factor. Finally, two parameters are conjointly determined that is formulated in the fourth model. To formulated mathematical models, the assumption is considered as follows: According to baffle protection, the affected zone can assign to the shelter within only one shelter. All mathematical models are formulated as follows:

3.4.1 Model I

This model is a deterministic model in which all input parameters being known and constant over time. This problem selects P facilities and seeks to minimize the total travel distance between affected zones and shelters. This model is well known as “Minisum facility location problem”. The model is a Mixed Integer Linear Programming (MILP) that describe as follows:

Index

I Set of affected zones i

J Set of candidate shelters j

Parameter

d_{ij} Distance between affected zone i and candidate shelter j

c_j Capacity of candidate shelter j

h_i Population in zone i

P The maximal number of facilities that can be placed

R Distance limit

M The large number

Decision variable

x_j 1 = if candidate shelter j is selected,

0 = otherwise

y_{ij} 1 = if demand zone i is assigned to candidate shelter j, 0 = otherwise

z_{ij} The population in zone i is assigned to candidate shelter j

Minimize $$\sum_i \sum_j d_{ij} * y_{ij} \tag{3.12}$$

Subject to $$\sum_j x_j \le P \tag{3.13}$$

$$y_{ij} \le x_j \qquad \forall i, j \tag{3.14}$$

$$d_{ij} * y_{ij} \le R \qquad \forall i, j \tag{3.15}$$

$$\sum_i z_{ij} \le c_j * x_j \qquad \forall j \tag{3.16}$$

$$\sum_j z_{ij} = h_i \qquad \forall i \tag{3.17}$$

$$z_{ij} \le M * y_{ij} \qquad \forall i, j \tag{3.18}$$

$$\sum_j y_{ij} = 1 \qquad \forall i \tag{3.19}$$

$$x_j, y_{ij} \in \{1,0\} \qquad \forall i, j \tag{3.20}$$

$$z_{ij} \ge 0 \qquad \forall i, j \tag{3.21}$$

Equation (3.12) is shown objective function that to minimizes travel distance between affected zone to candidate shelter. Equation (3.13) ensures that the number of shelters does not exceed P locations. Equation (3.14) states that affected community is only assigned to the selected location. Equation (3.15) states that the distance limit between affected community and shelter. Equation (3.16) put a constraint on the holding capacity of shelters, ensuring that the population served cannot exceed the maximum capacity of each shelter. Equation (3.17) put a constraint on the evacuation demand of each community. Equation (3.18) and (3.19) ensure that affected communities can be served by one shelter. Equation (3.20) and (3.21) state the mathematical definitions of these variables.

3.4.2 Model II

This model, we propose a stochastic programming model, in which the uncertain parameters are allocated to a probability distribution. The uncertain parameters can add in objective or constraint. The Model I is developed to be a stochastic model. Chance-constrained model is used to apply in this model for the purpose of considering uncertain distance as shown in equation (3.22).

$$P\left\{\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} * y_{ij} \le b\right\} \ge \alpha \tag{3.22}$$

Equation (3.22) is added to the deterministic model. Where b is defined as the maximum acceptable total distance, α is defined as a confidence level [24]. However, we can modify the equation (3.22) to non-linear programming for coding in optimizer tool by using normal distribution concept that refers from Kell and Wallace [25]. The equation (3.22) is reformulated following equation (3.23) - equation (3.33). We start by defining Y is total distance as Equation (3.23) which consists of average and variance as shown in Equation (3.24) and (3.25).

$$Y = \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} * y_{ij} - b \tag{3.23}$$

$$E(Y) = \sum_{i=1}^{n}\sum_{j=1}^{n} E[d_{ij}] * y_{ij} - b \tag{3.24}$$

$$V(Y) = \sum_{i=1}^{n}\sum_{j=1}^{n} V[d_{ij}] * y_{ij}^2 \tag{3.25}$$

That equation $\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} * y_{ij} \le b$ can be revised to normal distribution form as following Equation (3.26) to Equation (3.32).

$$P\left\{\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} * y_{ij} \le b\right\} \ge \alpha \tag{3.26}$$

$$P\left\{\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} * y_{ij} - b \le 0\right\} \ge \alpha \tag{3.27}$$

$$P\left\{Y \le 0\right\} \ge \alpha \tag{3.28}$$

$$P\left\{\frac{\left[\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} * y_{ij} - b\right] - \left[\sum_{i=1}^{n}\sum_{j=1}^{n} E[d_{ij}] * y_{ij} - b\right]}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} V[d_{ij}] * y_{ij}^2}} \le -\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} E[d_{ij}] * y_{ij} - b}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} V[d_{ij}] * y_{ij}^2}}\right\} \ge \alpha \tag{3.29}$$

$$P\left\{z \le -\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} E[d_{ij}] * y_{ij} - b}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} V[d_{ij}] * y_{ij}^2}}\right\} \ge \alpha \tag{3.30}$$

$$\phi^{-1}(\alpha) \le -\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} E\left[d_{ij}\right] * y_{ij} - b}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} V\left[d_{ij}\right] * y_{ij}^2}} \tag{3.31}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} E\left[d_{ij}\right] y_{ij} + \phi^{-1}(\alpha)\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} V\left[d_{ij}\right] y_{ij}^2} \le b \tag{3.32}$$

According to y_{ij} is decision variable $\{0,1\}$, Hence the equation (3.32) can be reformed to equation (3.33).

$$\sum_{i=1}^{n}\sum_{j=1}^{n} E\left[d_{ij}\right] y_{ij} + \phi^{-1}(\alpha)\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} V\left[d_{ij}\right] y_{ij}} \le b \tag{3.33}$$

3.4.3 Model III

For this section, the robust model is presented for supporting the uncertain situation in this study. The principle of Yu and Li [26] is applied to create a mathematical model for shelter site selection and evacuation planning. The model considers several situations with respect to probability principle. This model is represented in a Mixed Integer Linear Programming (MILP) that formulate as follows:

Index (addition)

S Set of scenario s

Parameter (addition)

h_{is} Population of zone i in scenario s

p_s Probability in scenario s

λ Variability weight

ω Weighting penalty (risk-aversion weight)

Decision variable (addition)

θ_s Non-negative deviation variable per scenario

δ_s Under-fulfillment of affected zone i in scenario s

Objective

Minimize

$$\sum_s p_s * TD + \lambda * \sum_s p_s * \left[\left(TD - \sum_s p_s * TD\right) + 2\theta_s\right] + \sum_s \omega * \sum_i \sum_s p_s * \delta_{is} \tag{3.34}$$

Subject to (13) - (16), (18) - (21)

$$\sum_j z_{ij} + \delta_{is} - h_{is} >= 0 \qquad \forall i, s \tag{3.35}$$

$$\sum_{i}\sum_{j} d_{ij} * y_{ij} = TD \tag{3.36}$$

$$TD - \sum_{s} p_s * TD + \theta_s \qquad \forall s \tag{3.37}$$

$$\theta_s, \delta_{is} \geq 0 \qquad \forall i, s \tag{3.38}$$

The first and second terms of objective function in equation (3.34) are mean and variance of the total distance, aim to measure solution robustness. The third term in equation (3.34) measures the model's robustness to the infeasibility of the control constraint. Equation (3.35) is a control constraint, the population at zone i in each situation is assigned to selected shelter and determine the under-fulfilled of demand in each zone. Equation (3.36) is the total travel distance between demand zone to candidate shelter. Equation (3.37) is the auxiliary equation. Lastly, the integrality restrictions are presented in equation (3.38).

3.4.4 Model IV

This model is formulated by combining between Model II and Model III that consider both uncertain distance and several situations. The equation (3.33) is added to the constraint of Model III and the objective function in equation (3.34). This model is a Mixed Integer Nonlinear Programming (MINLP).

3.5 Case study

Landslides and flash flood are a common geological phenomenon in many parts of the world [1]. In 2014, the landslide and flash flood have occurred in many countries such as Nepal, India, Sri Lanka and Thailand [27]. Many people have stricken by these phenomena which destroy both human life and asset. The department of mineral resource, the ministry of natural resources and the environment in Thailand have been surveyed risk areas of landslide and flash flood occurrence in 2012. They found that 6 provinces are risk area that consists of Chiang Mai, Chiang Rai, Nan, Phars, Uttaradit, and Chumphon. Chiang Rai province is the largest risk area, 25 municipalities or 528 villages can occur landslide and flash flood [27]. In this study, we present Banta municipality in Chiang Rai for validating our conceptual model in which more than 50% of the area is risk areas as shown in Figure 3.2. Note that the brown-shaded area does not mean that all of the areas will be hit by disaster, but it means that there are some areas in this brown-shade zone might hit by this disaster, in which it still has some safe area in this zone that do not locate in the way of landslide and flash flood. The area of Banta municipality is 58.99 square kilometers, with around 12,866 people in 20 communities. Ministry of Natural Resources and Environment developed a warning system for these disasters which can predict the emergency situation following the process in Figure 3.3. The population can evacuate to shelter within one to three hours after the department of mineral resource announced. The local government can predict the situation and warn for evacuation before the disaster occurs around one to three hours by observation of rain gauges system and surveillance operation points.

In this study, a case study in Banta municipality is given to test the conceptual model. This case study has 20 affected communities and 13 candidate shelters that shown in Figure

3.4 (The shelters are referred from the report of Department of Mineral Resources [28]). We assume that the distance limit in each route is 5 kilometers and the maximum of selected shelter is 10 shelters. According to the Model II considers uncertain distance with related to normal distribution that presented in section 3.4.2, the distance parameter is collected by finding several routes from origin to destination. Then, all distances of each assignment from affected zones to shelters are calculated for finding the average distance value and variance distance value. Finally, average and variance values are input in input data. The maximum acceptable total distance and the confidence level are assumed as 20 kilometers and 0.90, respectively. According to Model III and IV consider several situations under uncertain population or demand, we present to determine 4 scenarios. The 1st scenario, the number of people is less than the current population as 5 percent. The 2nd scenario, the number of people is equal to current population. The 3rd scenario, the number of people is more than the current population as 5 percent. Finally, the 4th scenario, the number of people is more than the current population as 10 percent. The probability in situation 1 – 4 is assumed as 0.15, 0.55, 0.3, 0.2, respectively.

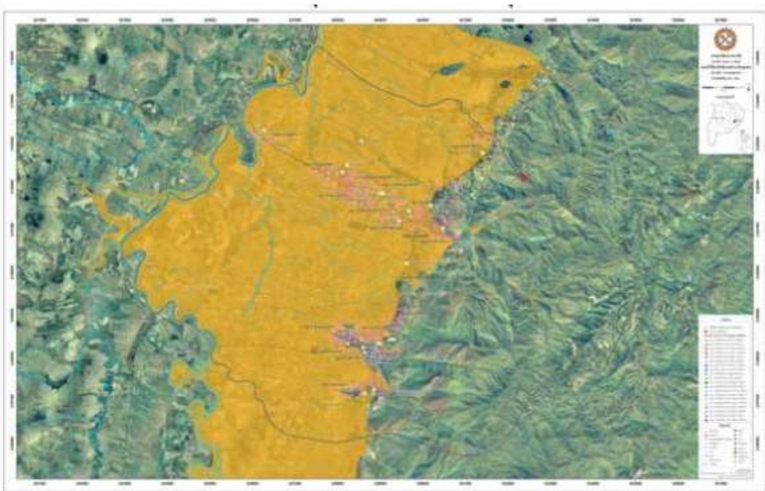


Figure 3.2 Risk areas in Banta municipality in Chiang Rai [28]

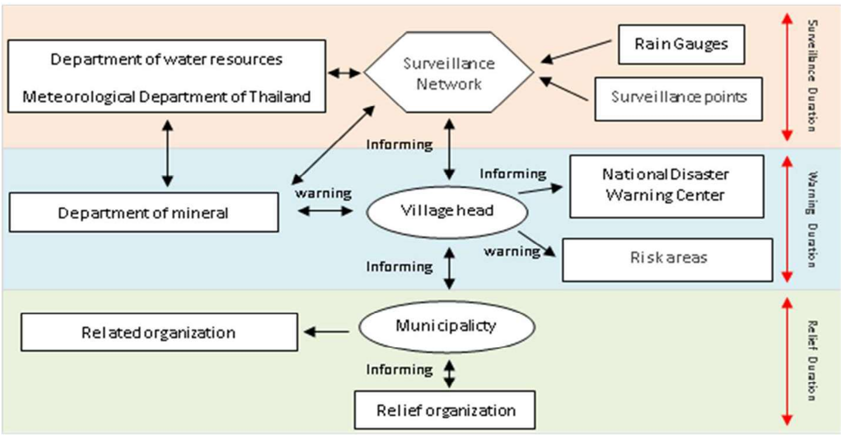


Figure 3.3 Emergency warning process [28]

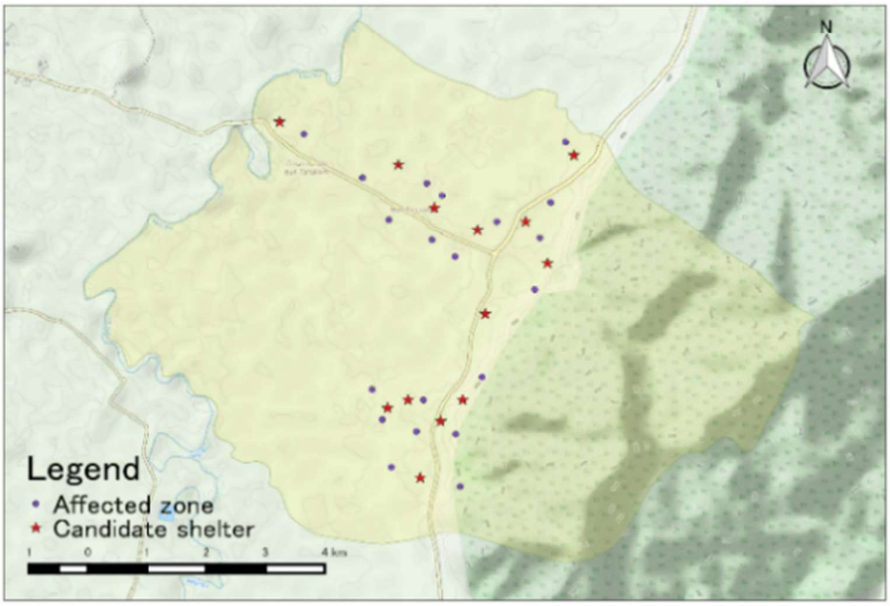


Figure 3.4 The position of villages and candidate shelters in Banta municipality [29]

3.6 Computation results

According to the methodology of this research, the result is separated into two main parts. The first part, the mathematical optimization is presented that shows the result of each model and the sensitivity analysis. The second part, the MCDM is showed which represents the determining weight of criteria, the determining the score of alternatives with respect to criteria, and the discussion of the result is proposed in this section.

3.6.1 Mathematical Optimization results

In this part, we code all mathematical models in LINGO 15 on a laptop with Intel Core i7 CPU 2.4 GHz and 4 GB of RAM. All run was solved in less than 15 minutes. The result of all mathematical model is shown in Table 3.3 and Figure 3.5. From Table 3.3, the optimal solution of the Model I is 18.01 kilometers which compose of shelter 1, 2, 4, 5, 6, 7, 8, 10, 11 and 12. All population in affected zones are assigned to a shelter. For the Model II, the optimal solution is 19.25 kilometers, the selected shelters are same as the Model I and all population are assigned to a shelter. For robust model, the ω value was tested for finding the suitable value. The result showed that the ω at 0.025 is suitable for this case study since at least all of population in situation 1 can be covered while some situation can be covered as well. For Model III, the optimal solution is 18.91 kilometers. In this solution are shelter 1, 2, 3, 4, 5, 6, 8, 10, 11 and 13. All populations in the 1st and the 2nd scenario are covered, but some populations in the 3rd and the 4th scenario are uncovered. In the Model IV, the optimal solution is 17.91 kilometer that composes of shelter as same as the Model III. For population assignment, all populations in the 1st scenario are covered, while some populations in 2nd, 3rd, and 4th scenario are uncovered. According to the output of results, the assignment of each model is different. However, the result of an assignment in some zone is similar, consists of zone 5, 8, 9, 10, 12, 15, 16, 18, 19 and 20.

For more detail, we also presented sensitivity analysis of a number of limited shelters that shown in Figure 3.6 and Table 3.4 From Figure 3.6, we first run all models by varying the number of limited shelters from 13 to 7, in a decrement of 1, to present the different objective function and assignment. The system needs at least 7 shelters for the relief response to be feasible. The result is found that the total distance is increased when the number of limited shelters is reduced. At first glance, the gradual increase in the maximum of selected shelter appears to reduce the total travel distance, However, when we reduce the number of selected shelter, the total travel distance is exponentially increased. For Model I and Model II at the number of limited shelters as 12 and 13, the total distance is stable at 15.91 and 17.6 kilometers, respectively. However, when the number of selected shelters less than 12, the total distance is continually increased. For Model III and Model VI at ϖ equal to 0.025, the tendency is continually increased when the number of selected shelters are reduced. The total travel distance of Model III is higher than Model IV during the number of selected shelters at 9-13 shelters. On the other hand, during the number of selected shelters at 7-8 shelters, the Model IV starts to decrease lower than the Model III. The average travel distance of Model II is the highest. Then by following Model III, Modell IV, and Model I, respectively. The decision makers can determine the plans following this sensitivity analysis by considering the maximum limit of selected shelter. To determine appropriated plan perfectly, the results of mathematical models will be determined in next step for choosing the appropriate plan.

Table 3.3 The result of a case study in Banta municipality, Chiang Rai Province, Thailand

Model type:	Model I	Model II	Model III	Model IV
Model class:	MILP	MINLP	MILP	MINLP
Optimal solution:	18.01 kilometer	19.25 kilometer	18.91 kilometer*	17.91 kilometer*
Selected shelter:	1,2,4,5,6,7, 8,10,11,12	1,2,4,5,6,7, 8,10,11,12	1,2,3,4,5,6, 8,10,11,13	1,2,3,4,5,6, 8,10,11,13
Zone 1	5	1	3	3
Zone 2	1	4	1	4
Zone 3	7	7	3	3
Zone 4	10	10	13	13
Zone 5	11	11	11	11
Zone 6	6	6	5	6
Zone 7	7	7	6	5
Zone 8	10	10	10	10
Zone 9	1	1	1	1
Zone 10	8	8	8	8
Zone 11	12	12	10	10
Zone 12	2	2	2	2
Zone 13	4	5	4	5
Zone 14	12	12	13	13
Zone 15	8	8	8	8
Zone 16	4	4	4	4
Zone 17	10	10	13	13
Zone 18	10	10	10	10
Zone 19	11	11	11	11
Zone 20	2	2	2	2

Note: The gray bar shows the same obtained solution from four mathematical models. * At ϖ equal 0.025, at least all of population in the 1st situation is covered.

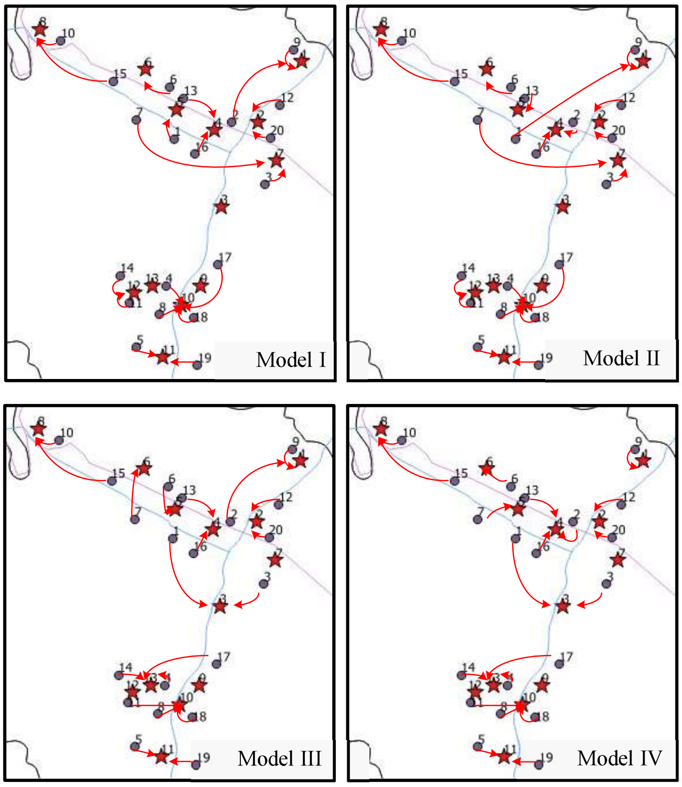


Figure 3.5 The results of four mathematical models

Table 3.4 The result of sensitivity analysis for the number of shelters

The number of shelter		7	8	9	10	11	12	13
Model I	Total distance	28.05	23.8	20.41	18.01	16.31	15.91	15.91
	Selected shelters	1,3,4,5,8, 10,13	1,3,4,5,6,8 ,10,13	1,2,4,5,6,7 ,8,10,13	1,2,4,5,6,7, 8,10,11,12	1,2,3,4,5,6, 7,8,10,11, 12	1,2,3,4,5,6,7, 8,9,10,11,12	1,2,3,4,5,6,7, 8,9,10,11,12, 13
Model II	Total distance	30.02	25.79	21.71	19.25	18	17.6	17.6
	Selected shelters	1,3,4,5,8, 10,13	1,3,4,5,6,8 ,10,13	1,2,4,5,6,7 ,8,10,13	1,2,4,5,6,7, 8,10,11,12	1,2,3,4,5,6, 7,8,10,11, 12	1,2,3,4,5,6,7, 8,9,10,11,12	1,2,3,4,5,6,7, 8,9,10,11,12, 13
Model III	Total distance	25.2	23.8	21.46	18.91	17.76	17.26	17.11
	Selected shelters	1,3,5,6,8 ,10,13	1,3,4,5,6,8 ,10,13	1,2,3,4,5,6 ,8,10,13	1,2,3,4,5,6, 8,10,11,13	1,2,3,4,5,6, 7,8,10,11, 13	1,2,3,4,5,6,7, 8,10,11,12, 13	1,2,3,4,5,6,7, 8,9,10,11,12, 13
Model IV	Total distance	26.6	24.03	20.48	17.91	16.84	16.31	16.28
	Selected shelters	1,3,5,6,8, 10,13	1,2,3,5,6,8 ,10,13	1,2,3,4,5,6 ,8,10,13	1,2,3,4,5,6, 8,10,11,13	1,2,3,4,5,6, 7,8,10,11, 13	1,2,3,4,5,6,7, 8,9,10,11,12	1,2,3,4,5,6,7, 8,9,10,11,12, 13

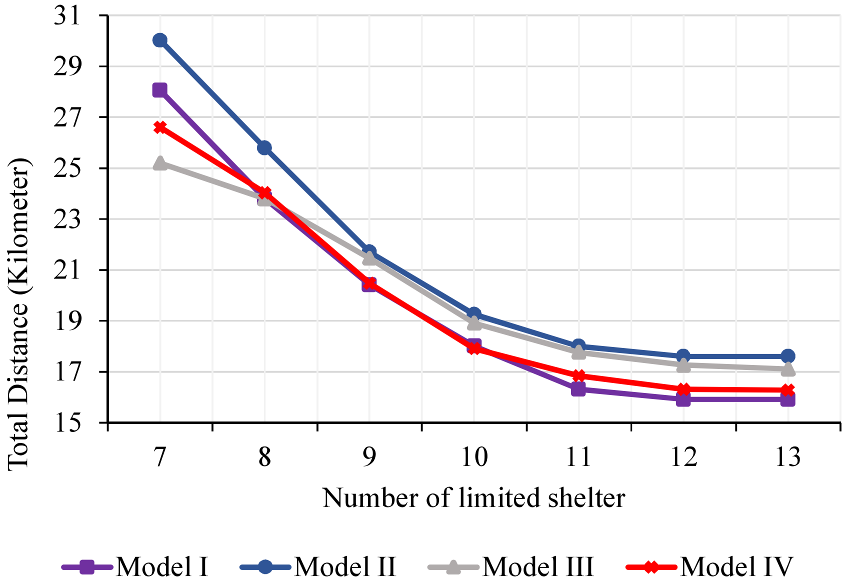


Figure 3.6 The derived total travel distance of each model under the different total number of selected shelter.

3.6.2 MCDM results

After mathematical optimization phase is used to create the plans, the multiple criteria decision-making phase is brought to evaluate proposed alternatives from mathematical models for selecting the best appropriate plan. In this study, we used the AHP approach for comparison and analysis, in which it can take into consideration the relative priorities of factors or alternatives and represents the best alternative. Owing to the uncertainty and vagueness of expert's opinion for comparison and analysis, we apply fuzzy set theory to AHP in this study that known as "Fuzzy AHP". All proposed alternatives are evaluated by 10 administers. This phase focuses on qualitative and quantitative measurement. Following literature review and brainstorming with local government, five main criteria are set as a principle or standard by which each model is judged or decided for reflecting the final solution (Target or level 1). The five main criteria could reflect on the main advantage of each model with respect to the perspective of decision makers. All of the criteria in AHP is independent (no correlation) in which AHP will use it for decision by pairwise comparison of different alternatives with respect to various criteria. The five main criteria consist of accessibility, availability, sustainability, total distance, and risk perspective. The measurements of this study, there are the quality of being able to be used or obtained of each shelter (Availability), the quality of being able to be reached or entered of related organization or accessory (Accessibility), the ability to be sustained, long-term planning supported, flexibility upheld, or confirmed of plan (Sustainability), a situation involving exposure to danger (Risk) and distance of evacuation (Distance).

The frame of the suitable plan selection for shelter site selection and evacuation planning can represent as following Figure 3.7. The description of the sub-criteria is presented in Table 3.5. From Figure 3.7, this study consists of four levels. Level 1 is a goal that seeks the appropriate plan for selecting shelter and evacuation planning. Level 2 is main criteria which consider accessibility, availability, sustainability, distance, and risk. Level 3 is a sub-criterion that separates from the main criteria; "Accessibility" criterion composes of evacuation, medical care services, and material reverse warehouse. "Availability" criterion consists of shelter. "Sustainability" criterion comprises of long-term planning. "Distance" consists of the total distance of evacuation. "Risk" criterion composes of distance from the source of danger, geological hazard, and topographic risk. The lowest is level 4 which proposes alternatives, the results from the mathematical optimization phase are used to be alternatives.

Table 3.5 The description of criteria for selecting shelter site and evacuation planning

Criteria	Description
A: Accessibility	
A1: Evacuation planning	Each affected zone should reach to shelter easily*
A2: Medical care services	The medical care services should reach to shelter easily for helping evacuee [17]
A3: Material reverse warehouse	Material reverse warehouse should reach to shelter easily for distributing emergency survival bag [17]
B: Availability	
B1: Shelter	The shelter should have serviced availability when disaster occurrence such as building, area, facility, etc. [18]
C: Sustainability	
C1: Long-term planning and flexibility	The model can apply at present as well as future. Moreover, the plan should have flexibility in perspective of population or demand changing [30]
D: Distance	
D1: Total distance of evacuation	The total travel distance between affected zone to shelter*
E: Risk	
E1: Distance from source of danger	The way between zones and shelters should be clear of poisonous gasses, inflammable, explosive or radioactive substances, high voltage transmission lines, and vulnerable structures, etc. The distance from the source of risk should meet national standards or requirements concerning major source of risks and fire protection [17]
E2: Geological hazard	The shelter for evacuation should avoid dangerous or adverse locations that are subject to natural disasters such as faulted zones, soil liquefaction, ground depression, landslide, debris flow, etc. [17]
E3: Topographic risk	The sites should be clear of danger of flood (breaking of river or reservoir dykes); they should be located on flat and expansive terrains; shelter for evacuation in the northern part of the country should avoid wind gaps; sites in the southern part of the country should avoid marshy lands, bottomlands and pounded terrains [17]

* Refer from administrator's brainstorming

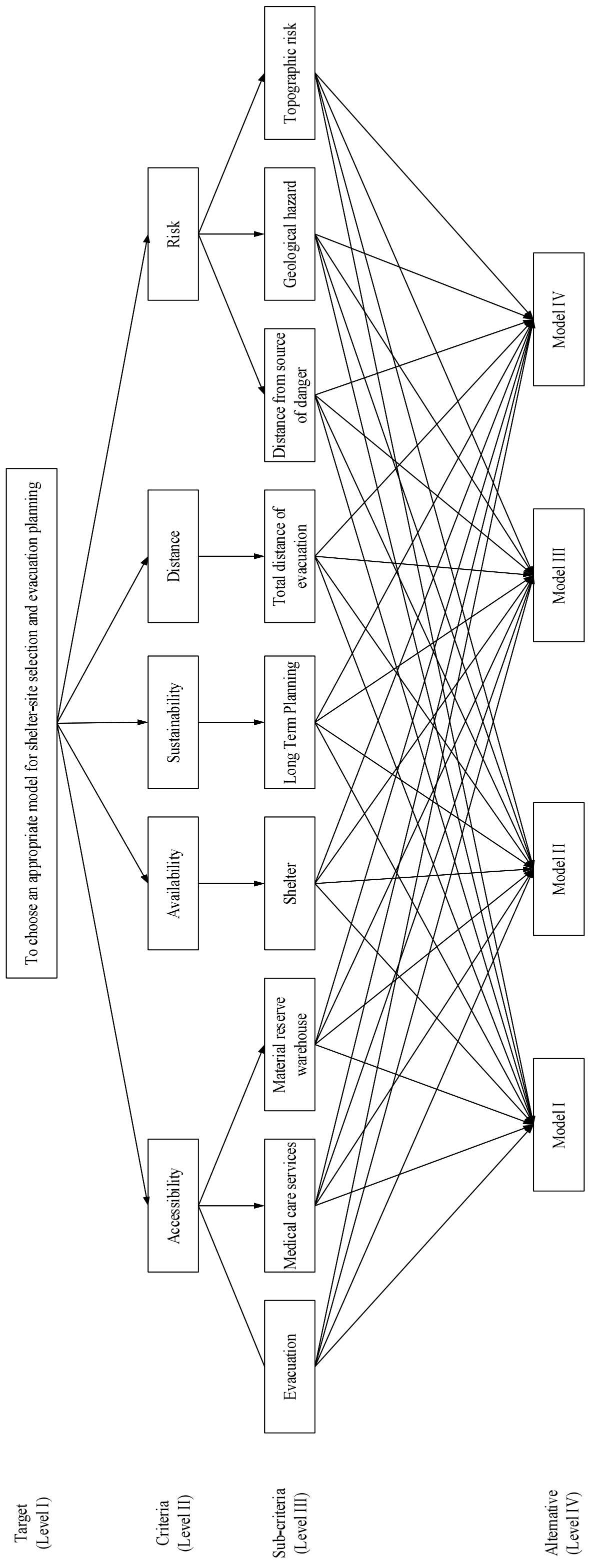


Figure 3.7 The structure of analytic hierarchy processes for selecting a suitable plan

Next, the decision makers evaluate the criteria weight and alternative score. In this study, the pairwise comparison matrix was evaluated by 10 administrators in Banta municipality. For determining the weight of criteria, this analysis should be repeated in 3 times; main criteria, sub-criterion of accessibility and sub-criterion of risk. For determining the score of alternatives with respect to sub-criteria, this calculation is repeated for 9 times. However, it will be burdensome to explain for each 12 of them. So, main criteria weight calculation and alternative score calculation of "Long-term planning and flexibility" criterion is handled to represent in this part. According to evaluation for determining the weight of main criteria, the average pairwise comparison is represented as following Table 3.6 and can be formed as Table 3.7. After that, the eigenvector /geometric mean of fuzzy comparison values of each criterion is calculated by Equation (3.5).

Table 3.6 Pairwise comparison of main criteria

Criteria 1	Versus	Criteria 2	Average weight
A	VS	B	$\tilde{2}$
A	VS	C	$\tilde{1}$
A	VS	D	$\tilde{1}$
A	VS	E	$\tilde{1}/2$
B	VS	C	$\tilde{1}/3$
B	VS	D	$\tilde{1}/2$
B	VS	E	$\tilde{1}/3$
C	VS	D	$\tilde{3}$
C	VS	E	$\tilde{1}$
D	VS	E	$\tilde{1}/3$

Table 3.7 Comparison matrix of main criteria

	A	B	C	D	E
A	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1/3,1/2,1)
B	(1/3,1/2,1)	(1,1,1)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1/4,1/3,1/2)
C	(1,1,1)	(2,3,4)	(1,1,1)	(2,3,4)	(1,1,1)
D	(1,1,1)	(1,2,3)	(1/4,1/3,1/2)	(1,1,1)	(1/4,1/3,1/2)
E	(1,2,3)	(2,3,4)	(1,1,1)	(2,3,4)	(1,1,1)

For example of weight calculation, the geometric mean of fuzzy comparison values of "Accessibility" is presented in equation (3.39). The eigenvector/geometric means of fuzzy comparison values of each criterion are shown in Table 3.8. Moreover, the total value, the reverse value, and increasing value are also represented in the three-last row of the table.

$$\tilde{q}_i = \left(\prod_{j=1}^{n} \tilde{x}_{ij}\right)^{1/n} = \left[(1\times1\times1\times1\times\frac{1}{3})^{1/5};(1\times2\times1\times1\times\frac{1}{2})^{1/5};\quad(1\times3\times1\times1\times1)^{1/5}\right] = \left[0.803;1.000;1.246\right] \tag{3.39}$$

In next step, Geometric means of fuzzy comparison values are calculated by equation (3.6) for finding the fuzzy weight in each criterion. The fuzzy weight of "Accessibility (A)" is presented for example as equation (3.40). All of the fuzzy weight is shown in Table 3.9. Afterward, the fuzzy weight of each criterion is de-fuzzified by equation (3.7) and then it is normalized by equation (3.8) as tabulated in Table 3.10.

$$\tilde{w}_1 = \left[(0.803 \times 0.146);(1 \times 0.180);(1.246 \times 0.228)\right] \tag{3.40}$$
$$= \left[0.117; 0.180; 0.284\right]$$

Table 3.8 Geometric means of fuzzy comparison values

Main criteria	$\tilde{q}_i$		
A: Accessibility	0.803	1.000	1.246
B: Availability	0.370	0.488	0.758
C: Sustainability	1.320	1.552	1.741
D: Distance	0.574	0.740	0.944
E: Risk	1.320	1.783	2.169
Total	4.386	5.563	6.858
Reverse	0.228	0.180	0.146
Increasing Order	0.146	0.180	0.228

In next step, Geometric means of fuzzy comparison values are calculated by equation (3.6) for finding the fuzzy weight in each criterion. The fuzzy weight of “Accessibility (A)” is presented for example as equation (3.40). All of the fuzzy weight is shown in Table 3.9. Afterward, the fuzzy weight of each criterion is de-fuzzified by equation (3.7) and then it is normalized by equation (3.8) as tabulated in Table 3.10.

$$\tilde{w}_1 = \left[(0.803 \times 0.146);(1 \times 0.180);(1.246 \times 0.228)\right] \tag{3.40}$$
$$= \left[0.117; 0.180; 0.284\right]$$

Table 3.9 Relative fuzzy weight of each criterion

Main criteria	$\tilde{q}_i$		
A: Accessibility	0.117	0.180	0.284
B: Availability	0.054	0.088	0.173
C: Sustainability	0.192	0.279	0.397
D: Distance	0.084	0.133	0.215
E: Risk	0.192	0.320	0.494

Table 3.10 Average and normalized relative weight of each criterion

Main criteria	M_i	N_i
A: Accessibility	0.187	0.181
B: Availability	0.096	0.093
C: Sustainability	0.284	0.275
D: Distance	0.139	0.134
E: Risk	0.328	0.317

Finally, the relative contribution weight is validated by CR test. Firstly, the largest value of the matrix is calculated by equation (3.11). After calculating λ_{max}, the CI is calculated by equation (3.10) in which the size of the matrix (n) is 5. Lastly, CR is found by equation (3.9) in which RI is 1.12. The calculation is represented as follows;

$$\lambda_{\max} = 26.071/5 = 5.214 \tag{3.41}$$

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{5.214-5}{5-1} = 0.054 \tag{3.42}$$

$$CR = \frac{CI}{RI} = \frac{0.054}{1.12} = 0.048 \tag{3.43}$$

As CR of main criteria is less than 0.1, hence the pairwise comparison made of main criteria is relative. This methodology is repeated for 2 more times for sub-criteria of "Accessibility" criterion and "Risk" criterion. All of the weights are presented in Figure 3.8. From Figure 3.9 and Figure 3.10, the highest weight of main criteria is "Risk" as 0.317, and then it is followed by "Sustainable" as 0.275, "Accessibility" as 0.181, "Distance" as 0.134, and "Availability" as 0.093, respectively. In the main criterion of "Accessibility", the weight is separated into three parts. The first part is Evacuation (A1), is placed as 54.63% or 0.099 in which it is the biggest portion. The second part is Medical care services (A2) that is located as 20.94% or 0.038. The third part is Material reverse warehouse (A3) that is placed as 24.43% or 0.044. Furthermore, the main criterion of "Risk" can be divided into three parts that consist of: distance from Source of danger (E1) as 11.16% or 0.037, Topographic risk (E3) as 40.41% or 0.128, and Geological hazard (E2) as 47.98% or 0.152. For "Availability" criterion, "Sustainability" criterion, and "Distance" criterion, only a sub-criterion is provided, so the sub-criterion of them is 100%.

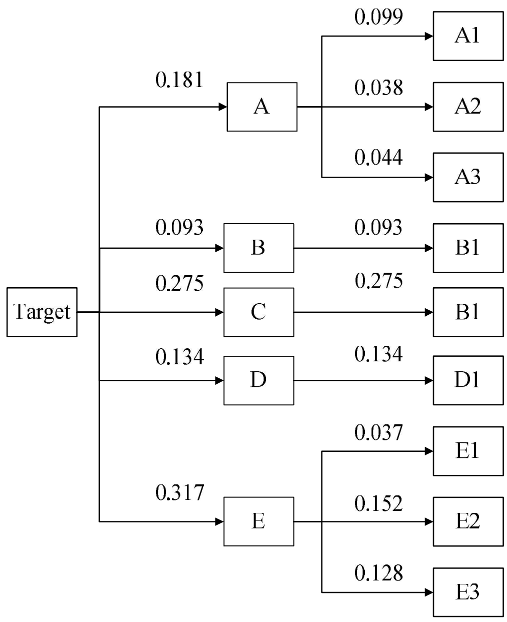


Figure 3.8 The structure of Fuzzy AHP with relative weight from the calculation

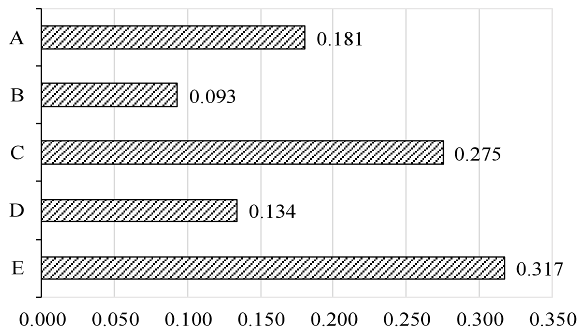


Figure 3.9 The comparison of relative weight in each main criterion

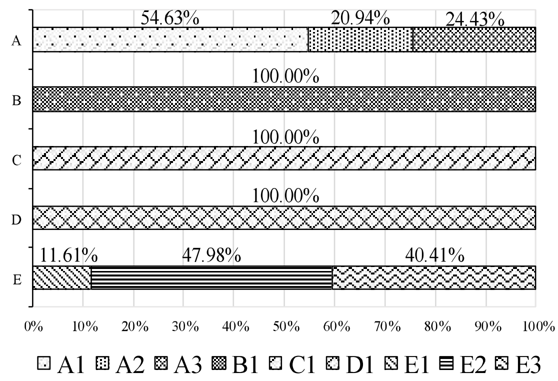


Figure 3.10 The structure of AHP with weight from the calculation

After obtaining the normalized non-fuzzy relative weight for main criteria and sub-criteria, the same method is applied to seek the alternative scores. For example of score calculation, determining the score of alternatives with respect to "Long-term planning and flexibility" criterion is represented. The pairwise comparison evaluation of alternatives with relates to "Long-term planning and flexibility" criterion is proposed in Table 3.11 and can be formed as pairwise comparison matrix in Table 3.12. After that, the eigenvector/geometric mean of fuzzy comparison score and a relative fuzzy score of each alternative are sought that shown in Table 3.13 and Table 3.14. Then, the average fuzzy score and the normalized relative score of each alternative with respect to "Long-term planning and flexibility" criterion is calculated and shown by following Table 3.15. In order to check the consistency of data, the pairwise comparison made is checked by CR test. The same methodology is proposed as following equation (3.41) - (3.43). The pairwise comparison of alternatives is made for 7 more times. Lastly, the normalized non-fuzzy relative weight of each alternative for each sub-criterion are found and presented in Table 3.16. The weight of sub-criteria and weight of each alternative for each sub-criterion are calculated for an individual score that tabulated in Table 3.17.

To select the appropriate model or plan, the result from Table 3.17 show that alternative 3 (Model III) has the largest total score as 0.311, and then it is followed by alternative 4 (Model IV) as 0.271, alternative 1 (Model I) as 0.240, and alternative 2 (Model II) as 0.185, respectively. Thus, the alternative 3 or Model III is the appropriate plan for this case study among four of them, with respect to five main criteria, nine sub-criteria and fuzzy preferences of the administrators (decision makers) in Banta municipality, Chiang Rai, Thailand.

Table 3.11 Pairwise comparison of alternatives with respect to “C1” criterion

Alternative 1	Versus	Alternative 2	Average weight
Model I	VS	Model II	$\tilde{1}$
Model I	VS	Model III	$\tilde{1}/2$
Model I	VS	Model IV	$\tilde{2}$
Model II	VS	Model III	$\tilde{1}/3$
Model III	VS	Model IV	$\tilde{2}$
Model III	VS	Model IV	$\tilde{2}$

Table 3.12 Comparison matrix of alternatives with respect to “C1” criterion

	Model I	Model II	Model III	Model IV
Model I	(1,1,1)	(1,1,1)	(1/3,1/2,1)	(1,2,3)
Model II	(1,1,1)	(1,1,1)	(1/4,1/3,1/2)	(1,2,3)
Model III	(1,2,3)	(2,3,4)	(1,1,1)	(1,2,3)
Model IV	(1/3,1/2,1)	(1/3,1/2,1)	(1/3,1/2,1)	(1,1,1)

Table 3.13 Geometric means of fuzzy comparison values

Alternative	$\tilde{q}_i$		
Model I	0.760	1.000	1.316
Model II	0.707	0.904	1.107
Model III	1.189	1.861	2.449
Model IV	0.439	0.595	1.000
Total	3.095	4.359	5.872
Reverse	0.323	0.229	0.170
Increasing Order	0.170	0.229	0.323

Table 3.14 Relative fuzzy weight of alternatives with respect to “C1” criterion

Alternative	$\tilde{q}_i$		
Model I	0.129	0.229	0.425
Model II	0.120	0.207	0.358
Model III	0.203	0.427	0.791
Model IV	0.075	0.136	0.323

Table 3.15 Average and normalized relative weight of alternatives with respect to ““C1” criterion

Alternative	M_i	N_i
Model I	0.245	0.229
Model II	0.218	0.203
Model III	0.450	0.421
Model IV	0.157	0.147

Table 3.16 The normalized non-fuzzy relative weight of each alternative for each sub-criterion

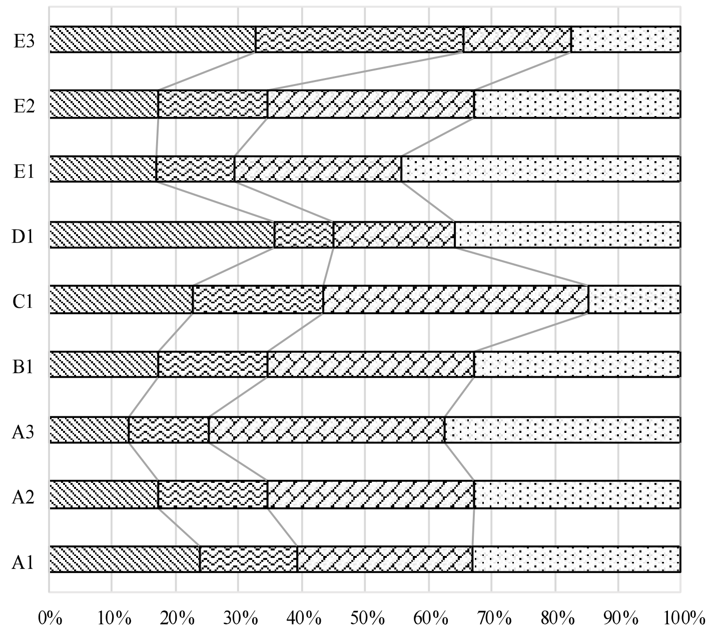
Sub-criteria	Model I	Model II	Model II	Model IV
A1	0.240	0.153	0.276	0.331
A2	0.173	0.173	0.327	0.327
A3	0.127	0.127	0.373	0.373
B1	0.173	0.173	0.327	0.327
C1	0.229	0.203	0.421	0.147
D1	0.374	0.098	0.202	0.374
E1	0.170	0.124	0.264	0.442
E2	0.173	0.173	0.327	0.327
E3	0.327	0.327	0.173	0.173

Table 3.17 Aggregated results for each alternative according to each sub-criterion

Sub criteria	Weight	Model I	Model II	Model II	Model IV
A1	0.099	0.240	0.153	0.276	0.331
A2	0.038	0.173	0.173	0.327	0.327
A3	0.044	0.127	0.127	0.373	0.373
B1	0.093	0.173	0.173	0.327	0.327
C1	0.275	0.229	0.203	0.421	0.147
D1	0.134	0.374	0.098	0.202	0.374
E1	0.037	0.170	0.124	0.264	0.442
E2	0.152	0.173	0.173	0.327	0.327
E3	0.128	0.327	0.327	0.173	0.173
Total		0.240	0.185	0.311	0.271

To select the appropriate model or plan, the result from Table 3.17 show that alternative 3 (Model III) has the largest total score as 0.311, and then it is followed by alternative 4 (Model IV) as 0.271, alternative 1 (Model I) as 0.240, and alternative 2 (Model II) as 0.185, respectively. Thus, the alternative 3 or Model III is the appropriate plan for this case study among four of them, with respect to five main criteria, nine sub-criteria and fuzzy preferences of the administrators (decision makers) in Banta municipality, Chiang Rai, Thailand.

From Figure 3.11 show that the Model I have the advantage for Total distance of evacuation and Topographic risk, while the Model II, it has a good point at Topographic risk only. The advantage of Model III is consisted of Medical care services, Material reverse warehouse, shelter, Long-term planning and flexibility, and Geological hazard, while the Model IV has a prominent point on Evacuation planning, Medical care services, Material reverse warehouse, Shelter, Total distance of evacuation, Distance from source of danger, and Geological hazard. Although the Model IV is more good point than the others, it is not an appropriate plan for this case study, because the decision makers concentrate on "Risk", "Sustainability", and "Availability" in which the Model III has a large weight portion in those criteria. Therefore, this is the reason why the alternative 3 or Model III significantly outperforms the others.



	A1	A2	A3	B1	C1	D1	E1	E2	E3
Model I	24.01%	17.26%	12.69%	17.26%	22.92%	37.41%	17.01%	17.26%	32.74%
Model II	15.32%	17.26%	12.69%	17.26%	20.35%	9.81%	12.38%	17.26%	32.74%
Model III	27.59%	32.74%	37.31%	32.74%	42.05%	20.16%	26.42%	32.74%	17.26%
Model IV	33.08%	32.74%	37.31%	32.74%	14.68%	37.41%	44.19%	32.74%	17.26%

Model I Model II Model III Model IV

Figure 3.11 The structure of AHP with a score from the calculation

3.6.3 Current problem – to – solution findings

As stated earlier, the target area of this case study has a risk to occur landslide and flash flood. However, in the reality of this problem, the shelter site selection and evacuation plan of local government are lacking to consider many factors both of quantitative and qualitative measurement such as the capacity of shelter, the expected population, risk, accessibility, etc. In which when the disaster occurs, the errors and inefficient performance issues might occur including unsuitable opened shelters, delays, amiss assignment, insufficient capacity of shelter, etc.

In this study, we determined that our proposed conceptual model can overcome those happenable problems, in which both quantitative and qualitative measurement is determined under expert's opinion. From the result of the case study, in the viewpoint of local governments, the selected plan (Model III) can overcome the previously expected plan. This plan confirms that the selected shelters can suppose evacuees such as capacity, accessibility, risk, and availability because some previously expected shelter sites are not suitable, in which it is lacking accessibility criterion, availability criterion and sufficient capacity of shelter.

Moreover, this plan can reduce the risk of suffering of victims during evacuation and rest in a shelter and this can support the future situation as well.

However, this model should consider the behavior of evacuation[31)] and the traffic congestion including mode of evacuation when the evacuees evacuate because those are the main factor that might affect the evacuation system. Although this our conceptual model can overcome all of these problems, it still has some problems. When the number of criteria or the number of alternatives (models) is increased, the evaluation might more difficult and complex to analysis, in which the analysis might error and affect to the final solution.

3.7 Conclusions

This study proposes a conceptual model for shelter sites selection and evacuation planning by considering both qualitative measurement and quantitative measurement. The optimization technique and multiple criteria decision making are applied in this study. Our conceptual model is tested with a real case study in Banta Municipality, Thailand. Firstly, an optimization technique is proposed to create plans for shelter site selection and evacuation planning. The mathematical models are formulated under different conditions and model types for considering the assignment of a community to a nearby shelter, the capacity of shelter, the distance limit, the number of shelter sites, and the number of demand. In this study, four mathematical models are formulated. After proposed mathematical models are coded and run in optimizer tool, the result of four models is evaluated by local government (Decision makers) in which Analytic Hierarchy Process (AHP) technique with the fuzzy approach is applied to analyze all models. The alternative models are inspected with respect to five main criteria namely; accessibility, availability, sustainability, and risk. Moreover, it also is inspected with respect to eight sub-criteria that compose of evacuation, medical care services, material reverse warehouse, shelter, long-term planning and flexibility, total distance of evacuation, distance from source of danger, geological hazard, and topographic risk. As the result, we found that the Model III outperforms the other models.

This chapter will be great significance in helping decision makers consider placement of emergency shelter and evacuation planning with respect to qualitative measurement, quantitative measurement and the uncertainty and vagueness of expert's opinion. In addition, by standing our methodology clearly and numerically, our conceptual model can be a guide of the methodology to be implemented to other problems as well. To recommend for others application, the mathematical model does not need to formulate same as this study. The researchers can design following research's opinion and used several objective functions or several constraints since it might show more efficient solution than this research. Moreover, although the Fuzzy AHP is useful for this study, it still consists some limitations and some problem such as subjective nature of decision makers, the complexity of analysis (too many criteria), and difficulty of quantifying importance for some criteria.

In further research, the models should add some conditions and criteria for more realistic. Moreover, Fuzzy TOPSIS, ELECTRE, PROMETHEE, and hybrid approach (Fuzzy AHP - TOPSIS) can be applied in this study for selecting an appropriated planning, the result can be compared.

Acknowledgment: We sincerely thank Banta municipality and Banta district at Chiang Rai province and Department of mineral resources in Thailand for supporting the data.

3.8 References

[1] Guha-Sapir, D., Hoyois, P., & Below, R. (2015). Annual Disaster Statistical Review 2014, The Numbers and Trends, Brussels, CRED.

[2] Özdamar, L., & Ertem, M. A. (2015). Models, solutions and enabling technologies in humanitarian logistics. European Journal of Operational Research, 244(1), 55-65.

[3] Safeer, M., Anbuudayasankar, S. P., Balkumar, K., & Ganesh, K. (2014). Analyzing transportation and distribution in emergency humanitarian logistics. Procedia Engineering, 97, 2248-2258.

[4] Jabbarzadeh, A., Fahimnia, B., & Seuring, S. (2014). Dynamic supply chain network design for the supply of blood in disasters: a robust model with real world application. Transportation Research Part E: Logistics and Transportation Review, 70, 225-244.

[5] Akgün, İ., Gümüşbuğa, F., & Tansel, B. (2015). Risk based facility location by using fault tree analysis in disaster management. Omega, 52, 168-179.

[6] Labib, A., & Read, M. (2015). A hybrid model for learning from failures: the Hurricane Katrina disaster. Expert Systems with Applications, 42(21), 7869-7881.

[7] Boonmee, C., Arimura, M., & Asada, T. (2017). Facility Location Optimization Model for Emergency Humanitarian Logistics. International Journal of Disaster Risk Reduction, Vol. 24, pp.485-498.

[8] Chanta, S., & Sangsawang, O. (2012). Shelter-site selection during flood disaster. Lect. Notes Manag. Sci, 4, 282-288.

[9] Santos, M. G., Meriño, M., Sore, N., & Quevedo, V. C. (2013, December). Flood Facility Location-Allocation in Marikina City Using MCLP with Lagrange. In The 14th Asia Pacific Industrial Engineering and Management Systems Conference, Philippines, December (pp. 3-6).

[10] Pan, A. (2010, December). The applications of maximal covering model in typhoon emergency shelter location problem. In Industrial engineering and engineering management (IEEM), 2010 IEEE international conference on (pp. 1727-1731). IEEE.

[11] Li, L., & Jin, M. (2010). Sheltering planning and management for natural disasters. In THC-IT 2010 Conference & Exhibition.

[12] Dalal, J., Mohapatra, P. K., & Mitra, G. C. (2007). Locating cyclone shelters: a case. Disaster Prevention and Management: An International Journal, 16(2), 235-244.

[13] Kılcı, F., Kara, B. Y., & Bozkaya, B. (2015). Locating temporary shelter areas after an earthquake: A case for Turkey. European Journal of Operational Research, 243(1), 323-332.

[14] Kongsomsaksakul, S., Yang, C., & Chen, A. (2005). Shelter location-allocation model for flood evacuation planning. Journal of the Eastern Asia Society for Transportation Studies, 6, 4237-4252.

[15] Feng, C. M., & Wen, C. C. (2005). A bi-level programming model for allocating private and emergency vehicle flows in seismic disaster areas. In Proceedings of the Eastern Asia Society for Transportation Studies, Vol 5 (Vol. 5, pp. 1408-1423).

[16] Bayram, V., Tansel, B. Ç., & Yaman, H. (2015). Compromising system and user interests in shelter location and evacuation planning. Transportation research part B: methodological, 72, 146-163.

[17] Chu, J., & Su, Y. (2012). The application of TOPSIS method in selecting fixed seismic shelter for evacuation in cities. Systems Engineering Procedia, 3, 391-397.

[18] Bozorgi-Amiri, A., & Asvadi, S. (2015). A prioritization model for locating relief logistic centers using analytic hierarchy process with interval comparison matrix. Knowledge-Based Systems, 86, 173-181.
[19] Erensal, Y. C., Öncan, T., & Demircan, M. L. (2006). Determining key capabilities in technology management using fuzzy analytic hierarchy process: A case study of Turkey. Information Sciences, 176(18), 2755-2770.
[20] Junior, F. R. L., Osiro, L., & Carpinetti, L. C. R. (2014). A comparison between Fuzzy AHP and Fuzzy TOPSIS methods to supplier selection. Applied Soft Computing, 21, 194-209.
[21] Buckley, J. J. (1985). Fuzzy hierarchical analysis. Fuzzy sets and systems, 17(3), 233-247.
[22] Chang, K. F., & Yang, H. W. (2011). A study of cosmetic bundle by utilizing a fuzzy Analytic Hierarchy Process (AHP) to determine preference of product attributers toward customer value. African Journal of Business Management, 5(22), 8728.
[23] Saaty, R. W. (1987). The analytic hierarchy process—what it is and how it is used. Mathematical modelling, 9(3-5), 161-176.
[24] Jaiyen, E. (2012) Traveling saleman with uncertainty of time traveling problem solving using ant colony, Dissertation. Chiang Mai University.
[25] Kall, P., & Stein W. W. (1994) Stochastic Programming, John Wiley & Sons, Chichester.
[26] Yu, C. S., & Li, H. L. (2000). A robust optimization model for stochastic logistic problems. International journal of production economics, 64(1), 385-397.
[27] Fowze, J. S. M., Bergado, D. T., Soralump, S., Voottipreux, P., & Dechasakulsom, M. (2012). Rain-triggered landslide hazards and mitigation measures in Thailand: From research to practice. Geotextiles and geomembranes, 30, 50-64.
[28] Department of Mineral Resources, Ministry of Natural Resources and Environment, Thailand, Retrieved from http://www.dmr.go.th
[29] Boonmee, C., Naotaka, I., Takumi, A., & Mikiharu, A. (2016) Multi-model optimization for shelter-site selection: A case study in Banta municipality, Thailand, Proc. of Infrastructure Planning in Japan Society of Civil Engineers, 53, 2175-2181.
[30] Orencio, P. M., & Fujii, M. (2013). A localized disaster-resilience index to assess coastal communities based on an analytic hierarchy process (AHP). International Journal of Disaster Risk Reduction, 3, 62-75.
[31] Boonmee, C., Takumi, A., & Mikiharu, A. (2017) A bi-criteria optimization model for hierarchical evacuation and shelter site selection under uncertainty of flood events, Journal of the Eastern Asia Society for Transportation Studies, 12, 4237-4252.

Chapter 4

Improving Evacuation Planning and Shelter Site Selection for Flood Disaster: Thai Flood Case Study

4.1 Introduction

Recently, the world has affected by many disasters such as earthquakes, storms, floods, landslides, etc. Since the 1950s, the number of disasters has been continuously increasing, as shown in Figure 4.1 [1]. According to the international disaster database, they propose that Asia and America are the most affected continues by natural disasters such as hydrological disaster, geophysical disaster, meteorological disaster, climatological disaster [2]. The World Health Organization (WHO) defines a 'disaster' as any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area [3]. Owing to the increasing severity of recent of disasters, academicians have paid a great deal of attention to "Disaster Management" for the purposes of helping at-risk persons to avoid or recover from the effects of a disaster. The activity of disaster management consists of four stages: mitigation, preparation, response, and recovery [4,5].

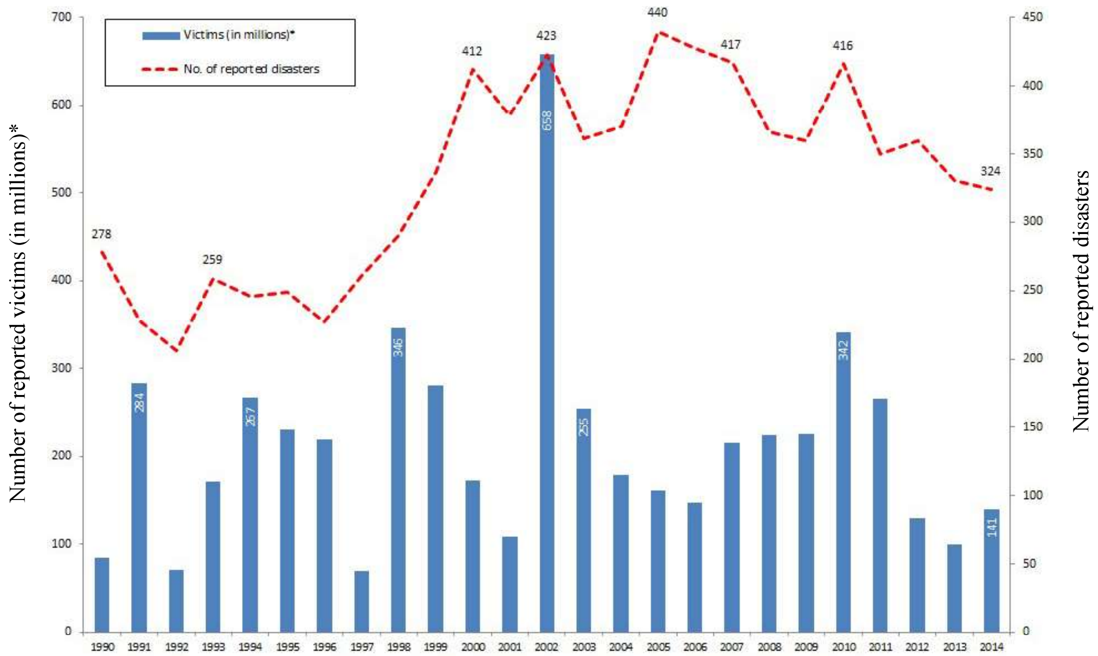


Figure 4.1 Trends in occurrence and victims [1]

Flood disaster is the largest share of natural disaster occurrence in 2014 to estimate to be 47.2% (Figure 4.2). The number of floods and mass movement of hydrological origin were 153 disasters in 2014. The massive flood disaster occurred in China and Thailand in 2011. Flood shelter site selection and flood evacuation planning are a major activity that should prepare and plan before the floods occur in order to help people in an affected zone to avoid from the effect of the flood disaster. In flood shelter site selection and flood evacuation planning, there are many major criteria that should be considered such as evacuation distance, uncertainty of occurrence, evacuee's behavior, utilization of shelter and hazard of flood disaster. Our previous model proposed solutions for evacuation planning and shelter site selection which considers the assignment of communities and evacuee's behavior condition [5]. However, that model is lacking some major criteria that should be considered such as utilization of shelter. Therefore, this chapter aim to develop that model for designing flood shelter site selection and flood evacuation planning under probabilistic scenarios that reflect the uncertainties of flood events and their consequences in which this study aims to consider the distribution of shelter sites and communities, evacuee's behavior, utilization of shelter and capacity restrictions of shelter simultaneously.

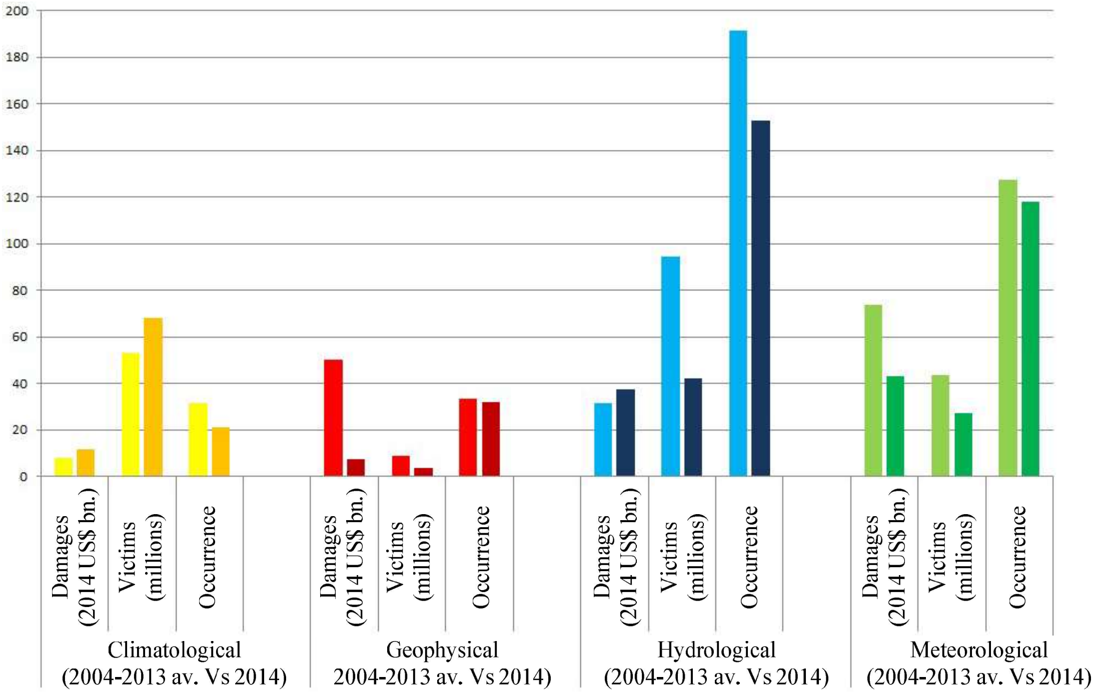


Figure 4.2 Natural disaster impacts by disaster sub-group: 2014 versus 2003-2013 annual average [1]

The remainder of this chpter is organized as follows: Section 4.2 presents a review of related literature. Section 4.3 shows conceptual model and mathematical model. To illustrate how the proposed mathematical model works on the real case, we propose the case study in section 4.4. Section 4.5 shows the computational results and sensitivity analysis. Finally, the conclusion and discussions are presented in Section 4.6.

4.2 Literature reviews

This section presents an overview of relevant literature. Recent research has also included surveys on effective DM such as Caunhye et al. [6], and Özdamar and Ertem [7], Boonmee et al. [8] and Zheng et al. [9]. There are many papers dealing with sheltering operation and evacuation planning. Table 4.1 displays important characteristics of existing studies in this area comprising of objective function, time period horizon, category of single or multistage approach, category of deterministic or stochastic programming, mathematical model, solutions algorithms and case study.

Chanta and Sungsawang [10] proposed bi-objective optimization model to select temporary shelter sites for flood disaster in Bangkruai, Thailand. The objective functions aim to maximize the number of victims that can be covered within a fixed distance and to minimize the total distance of all victims to their closest shelters. Boonmee et al. [11] proposed multi-model optimization for shelter site selection and evacuation planning. The mathematical models were formulated under different constraints and model types. The objective function is to minimize the total travel distance. Finally, all models were proposed to policymakers for choosing the best evacuation plan. Chowdhury et al. [12] proposed multi-objective mathematical programming model and simulation model to quantify objectives and provided decision support for cyclone shelter location in Bangladesh. Santos et al. [13] proposed a maximal covering location problems (MCLP) with Lagrange optimization model for flood shelter site selection. The proposed mathematical model aims to maximize the population covered by the limited number of facility locations. Moreover, this study also considers flood level constraint. Similarly, Wang et al. [14] proposed an MCLP-based optimization model to identify the best precipitation stations. The proposed model considers some special constraints and the associated rainfall monitoring demand. This study was applied in Jinsha River Basin. Kulshrestha et al. [15] presented a robust shelter location model to determine optimal shelter locations and their capacities under demand uncertainty. This proposed model not only determines the number of shelters and capacities but also considers the route to access to shelters. Kongsomsaksakul et al. [16] studied shelter location-allocation model for flood evacuation planning. The mathematical model was formulated as a bi-level programming model. The upper bound is a location problem while the lower bound is a combined distribution and assignment (CDA) model. The proposed model was solved by using a genetic algorithm. Addition, bi-level programming model was proposed by Li et al. [17] for developing dynamic traffic assignment problem for the selection of shelter locations with explicit consideration of a range of possible hurricane events and the evacuation needs under each of those events. Others bi-level programming model was proposed by Liu et al. [18] and Feng and Wen [19].

Stochastic programming is one of the most widely used approaches for planning in evacuation planning and shelter site selection due to its ability to account for uncertain criteria. Salmam and Yücel [20] proposed a stochastic integer programming model for determining the location of emergency response facilities among a set of potential ones. The objective aims to maximize the expected total demand covered within a predetermined distance parameter, over all possible network realizations. Furthermore, the stochastic programming in this field is proposed by Mirzapour et al. [21]. This study presents a mixed integer nonlinear programming model of a capacitated facility location-allocation problem which simultaneously considers the probabilistic distribution of demand locations and a fixed line barrier in a region. For integrated decision shelter site selection and evacuation planning under hierarchical evacuation concept, Chen et al. [22] proposed a hierarchical location model for earthquake-shelter planning. This proposed mathematical model considers financial constraints imposed upon the construction of shelters and changing needs of refugees. The real case in Beijing, China is applied to validate this proposed model. Another multi-step evacuation is proposed by Hu et al. [23]. The proposed mixed-integer linear program model is formulated for multi-step evacuation and temporary resettlement under minimization of panic-induced psychological penalty cost, psychological intervention cost, and costs associated with transportation and building shelters.

According to the related existing literature review in flood evacuation planning is lacking a determined perspective on the uncertainty of occurrence, evacuee's behavior, utilization of shelter, capacity restriction of shelter, and hierarchical evacuation concept simultaneously. Therefore, this chapter aims to propose stochastic linear mixed-integer programming model for optimizing integrated decision related to shelter site selection under a hierarchical evacuation concept during flood disaster. This proposed model not only provides a flood shelter site but also considers hierarchical evacuation concept for flood disaster that balances the preparedness and risk despite the uncertainties of flood events. Besides, we consider the distribution of shelter sites and communities, evacuee's behavior, utilization of shelter, and capacity restrictions of shelter as well.

Table 4.1 The review study of optimization model on shelter site selection and evacuation planning

No	Author	Objective	Period	Level	D/S	Model	Solution	Case study
1	Chanta and Sungsawang [10]	Min distance, Max covering demand	Single	Single	D	Linear	Epsilon constraint	Bangkruai, Thailand
2	Boonmee et al. [11]	Min distance	Single, Multi	Single	D/S	Linear/ Non-Linear	Exact algorithm	Banta, Thailand
3	Chowdhury et al. [12]	Min risk, Min cost, Max protection of units	Single	Single	D	Non-Linear	Greedy heuristic	Bangladesh
4	Santos et al. [13]	Max covering demand	Single	Single	D	Linear	Exact algorithm	Marikina, Philippine
5	Wang et al. [14]	Max covering demand	Single	Single	D	Linear	Exact algorithm	Jinsha River Basin
6	Kulshrestha et al. [15]	Min cost	Single	Single	D	Linear	A cutting-plane algorithm	the Sioux Falls network
7	Kongsomsaksakul et al. [16]	Min evacuation time	Single	Bi	D	Non-Linear	Genetic Algorithm	Utah
8	Li et al. [17]	Min travel time	Multi	Bi	S	Non-Linear	Lagrangian relaxation algorithm	North Carolina
9	Liu et al. [18]	Max throughput, Min total trip time	Multi	Bi	D	Linear	Exact algorithm	Ocean City
10	Feng and Wen [19]	Max number of vehicles	Single	Bi	D	Linear	Genetic Algorithm	Numerical example
11	Salmam and Yücel [20]	Max satisfied demand	Single	Single	S	Linear	Tabu search	Istanbul's earthquake preparedness
12	Mirzapour et al. [21]	Min maximum weighted distance	Single	Single	S	Non-Linear	Exact algorithm	Mazandaran province, northern part of Iran
13	Chen et al. [22]	Min weighted distance	Multi	Single	D	Linear	Exact algorithm	Beijing, China
14	Hu et al. [23]	Min cost	Multi	Single	D	Linear	Exact algorithm	Sichuan, China

Note: D = Deterministic problems, S = Stochastic problems

4.3 The proposed model

4.3.1 Conceptual model

In this section, we describe the conceptual model for the flood shelter site selection and flood evacuation planning. This conceptual model is designed with respect to the hierarchical evacuation concept. In this study, we assume that each evacuation step is called "Evacuation period". The evacuation periods are provided by the local government or policy makers that can be separated with respect to the step of flooding or the step of impact level from hazard map. For example, in Figure 4.3 and 4.4, we represent three-level hierarchical evacuation model that consists of three evacuation periods and three impact levels. In the 1st evacuation period, when the flood warning system alarms for the 1st evacuation, the refugees who stay in impact level 1 will be assigned to one of the nearby shelters. In the 2nd evacuation period, when the flood warning system alarms for the 2nd evacuation, the refugees who stay in impact level 2 will be assigned to the nearby shelters. While the refugees of selected shelters in the 1st evacuation period where locate in impact level 2, they will be relocated to new shelters. In the 3rd evacuation period, when the flood warning system alarms for the 3rd evacuation, the refugees who stay in impact level 3 will be evacuated to one of the nearby shelters. While the refugees of selected shelters in the 1st evacuation period and the 2nd evacuation period where locate in impact level 3, they will be relocated to the new shelters as well. Before the mathematical model is formulated, we make the following assumptions on the problem:

1. According to evacuee's behavior during flood events, some refugees always evacuate neither before the disaster or after the disaster. Consequently, we assume that the refugees can evacuate to shelter any evacuation periods under varying needs of the refugees.
2. The affected community can be served by one shelter in each period.
3. Some shelter can be located in flooding risk area.
4. Shelters have a limited capacity for accommodating the demand assigned to them.
5. The flood warning system will alarm following the step of impact level with respect to decision making's local government or policymakers.
6. The road network is not considered in this model

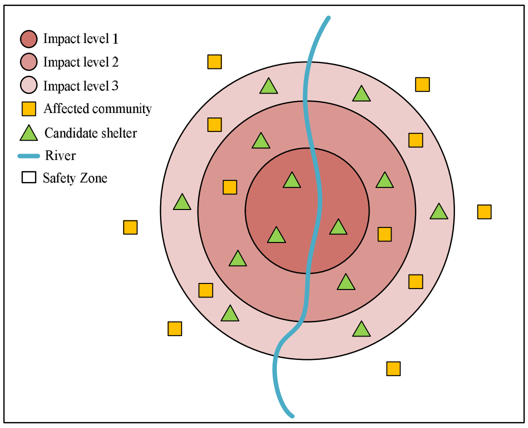


Figure 4.3 The hazard map of conceptual model for hierarchical evacuation planning and shelter site selection during floods

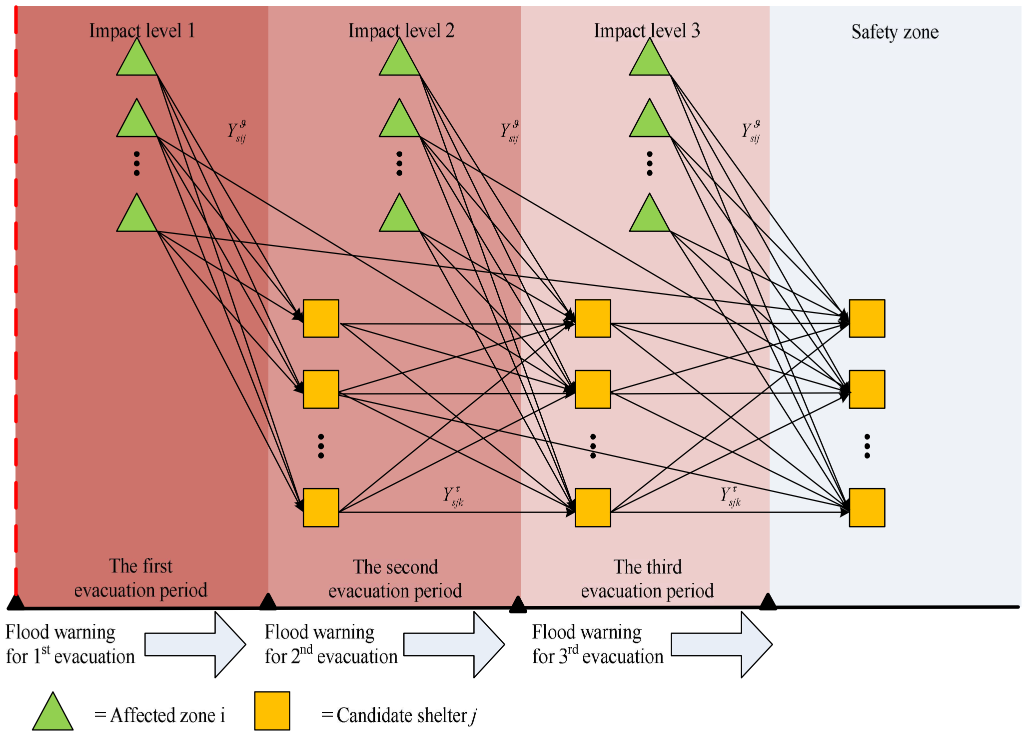


Figure 4.4 The conceptual model of for hierarchical evacuation planning and shelter site selection during floods

4.3.2 Mathematical model

In this section, we proposed the stochastic linear mixed-integer programming model for optimizing integrated decision related to shelter site selection under a hierarchical evacuation concept. The indices, parameters, decision variables, objective function, and constraints are presented as follows:

Indices and index sets

I Set of affected communities; $i \in I$

J Set of candidate shelters; $j,\ k \in J$

ξ Set of evacuation periods and impact level; $s \in \xi$

Parameters

MS Maximum limit of selected shelters

M A Large positive number

μ Threshold value for minimum utilization of shelter

P_s Probability of flooding in impact level $s \in \xi$

D_i Population in affected community $i \in I$

PD_{si} Proportion of population in affected community $i \in I$ need to evacuate in evacuation period $s \in \xi$

η_j Capacity of shelter $j \in J$

∂_{sj} Equal to 1 if candidate shelter $j \in J$ locate in impact level $s \in \xi$, 0 otherwise

D_{ij}^{ϑ} Distance from affected community $i \in I$ to candidate shelter $j \in J$ (km)

D_{jk}^{τ} Distance from candidate shelter $j \in J$ to candidate shelter $k \in J$ (km)

Decision variables

X_j 1 if shelter $j \in J$ is selected, 0 otherwise

TP_{sj} Total population of shelter $j \in J$ in evacuation period $s \in \xi$

Y_{sij}^{ϑ} 1 if affected community $i \in I$ is assigned to candidate shelter $j \in J$ during evacuation period $s \in \xi$, 0 otherwise

Y_{sjk}^{τ} 1 if shelter $j \in J$ is assigned to candidate shelter $k \in J$ during evacuation period $s \in \xi$,0 otherwise

Z_{sij}^{ϑ} Number of people evacuates from affected community $i \in I$ to shelter $j \in J$ during evacuation period $s \in \xi$

Z_{sjk}^{τ} Number of people evacuates from affected shelter $j \in J$ to candidate shelter $k \in J$ during evacuation period $s \in \xi$

Objective function

Most evacuation models measure the efficiency of evacuation by total travel cost in terms of response distance or time [24]. Since the floods typically are known about several hours before communities will be affected, evacuees will have sufficient time for evacuation. Thus, this study aims to focus on travel distance criterion with respect to the population of each community. This objective function is multiple values between population-weighted travel distance and the probability of flooding in each impact level with respect to a disaster scenario. The objective function can be formulated as equation (4.1). The expected population-weighted travel distance is expressed in equation (4.2), where, this consists of the distance between affected community to shelter and the distance between shelter to shelter as shown in equation (4.3).

Minimize $$E_{\xi}\left[Q\left(X_j, s\right)\right] \tag{4.1}$$

$$E_{\xi}\left[Q\left(X_j, s\right)\right] = \sum_{s \in \xi} P_s * Q\left(X_j, s\right) \tag{4.2}$$

$$Q\left(X_j, s\right) = \left\{\left[\sum_{i \in I}\sum_{j \in J} D_{ij}^{\vartheta} * Z_{sij}^{\vartheta}\right] + \left[\sum_{j \in J}\sum_{k \in J} D_{jk}^{\tau} * Z_{sjk}^{\tau}\right]\right\} \quad \forall s \in \xi \tag{4.3}$$

Constraints

Maximum number of selected shelters: Equation (4.4) states that the total number of selected shelters cannot exceed the maximum limit of selected shelter. Equation (4.5) guarantees that the population can be served to shelter when it is selected.

$$\sum_{j \in J} X_j \leq MS \tag{4.4}$$

$$\sum_{s \in \xi} TP_{sj} \geq X_j \qquad \forall j \in J \tag{4.5}$$

Shelter capacity: Equation (4.6) states that the total number of evacuees is covered by shelter *j* should not exceed its capacity.

$$\sum_{s \in \xi} TP_{sj} \geq X_j * \eta_j \qquad \forall j \in J \tag{4.6}$$

Total population in each evacuation periods: Equation (4.7) states that the total number of population in each evacuation period.

$$\sum_{i \in I} Z_{sij}^{\vartheta} * \left(1 - \partial_{sj}\right) + \sum_{k \in J} Z_{skj}^{\tau} * \left(1 - \partial_{sj}\right) = TP_{sj} \qquad \forall j \in J, s \in \xi \tag{4.7}$$

Evacuation requirements: Equation (4.8) ensures that the number of evacuees needs to evacuate to a shelter in each evacuation period should be equal to the expected evacuation requirements with respect to the evacuee's behavior.

$$\sum_{j \in J} Z_{sij}^{\vartheta} * \left(1 - \partial_{sj}\right) = PD_{si} * D_i \qquad \forall i \in I, s \in \xi \tag{4.8}$$

Flow balance: Equation (4.9) and (4.10) states the balance constraint in which the number of population departure should be equal to the number of the population come. Note that ∂_{sj} present assignment protection for shelters, when the shelter is located in safety zone, the population does not need to evacuate to a new shelter.

$$TP_{1,j} * \partial_{2,j} = \sum_{k \in J} Z_{2,jk}^{\tau} * \left(1 - \partial_{2,k}\right) \qquad \forall j \in J \tag{4.9}$$

$$\left(TP_{2,k} * \partial_{3,k}\right) + \left(TP_{1,k} * \left(\partial_{3,k} - \partial_{2,k}\right)\right) = \sum_{k \in J} Z_{3,jk}^{\tau} * \left(1 - \partial_{3,k}\right) \qquad \forall j \in J \tag{4.10}$$

Controls the utilization of selected shelter areas: Equation (4.11) states that if a shelter site is open, then the utilization of that shelter area needs to exceed the pre-determined threshold value. Note that the utilization is a ratio between the number of evacuees is covered and shelter capacity.

$$\sum_{s \in \xi} \frac{TP_{sj}}{\eta_j} \geq \mu * X_j \qquad \forall j \in J \tag{4.11}$$

Assignment limit: Equation (4.12) - (4.13) state that the binary variable of the assignment is set to 1 when the people in each community or each shelter is assigned to each shelter. Equation (4.14) - (4.15) ensure that the affected community can be served by one shelter in each period.

$$Z_{sij}^{\vartheta} \leq M * Y_{sij}^{\vartheta} \qquad \forall i \in I, j \in J, s \in \xi \tag{4.12}$$

$$Z_{sjk}^{\tau} \leq M * Y_{sjk}^{\tau} \qquad \forall j \in J, k \in J, s \in \xi \tag{4.13}$$

$$\sum_{j \in J} Y_{sij}^{\vartheta} \leq 1 \qquad \forall i \in I, s \in \xi \tag{4.14}$$

$$\sum_{k \in J} Y_{sjk}^{\tau} \leq 1 \qquad \forall j \in J, s \in \xi \qquad (4.15)$$

Non-negativity and binary conditions: Equation (16) and (17) describe non-negativity and binary conditions of the decision variable.

$$X_j, Y_{sij}^{\vartheta}, Y_{sjk}^{\tau} \in \{0,1\} \qquad \forall i \in I, j \in J, k \in J, s \in \xi \qquad (4.16)$$

$$Z_{sij}^{\vartheta}, Z_{sjk}^{\tau} \geq 0 \qquad \forall i \in I, j \in J, k \in J, s \in \xi \qquad (4.17)$$

4.4 Case study

To show how the proposed mathematical model can work on the real case problem, this section presents a case study in Chiang Mai province in northern Thailand to validate our proposed model. Chiang Mai Province usually occurs flood disaster in May-October rainy season which is dominated by masses of moist air moving from the Indian Ocean, and tropical depressions moving westward from the South China Sea.

Chiang Mai province develops a flood warning system for Ping river which can predict the real-time situation. This system uses two gauging stations, P.67 located at Ban Mae-tae in Sansai district and P.1 in downtown Chiang Mai, in which the water takes about seven hours for traveling to P.1 station (Figure 4.5). The Natural Disaster Research Unit of Civil Engineering Department of Chiang Mai University (CENDRU) has surveyed and collected floods data in Chiang Mai for a long time ago [25]. The Chiang Mai flood hazard map is produced based on historical data from Station P.1 and P.67 since 2006 as shown in Figure 4.6, the risk area is divided into seven levels.

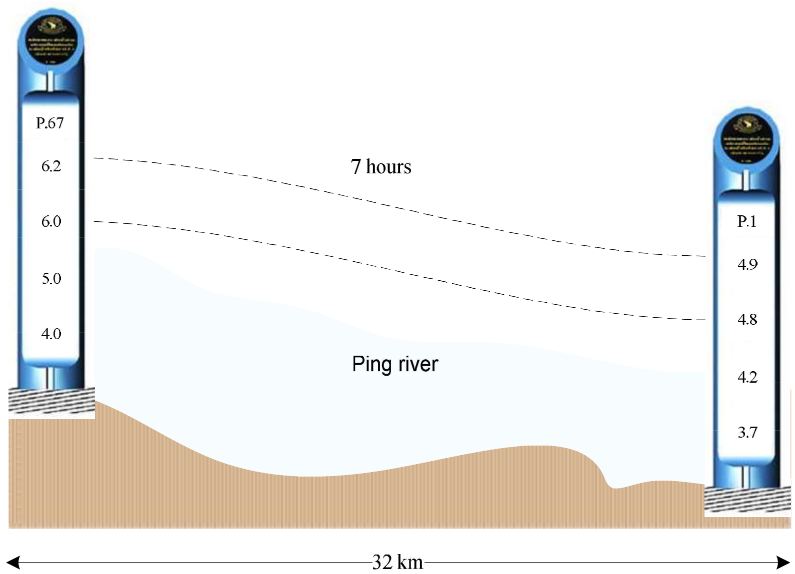


Figure 4.5 The position of station P.1 and P.67 on the Ping river

According to the classification of the impact level by CENDRU. To apply to our conceptual model, if we determine with respect to seven impact levels, it is too many for evacuation in each level and burdensome for evacuees, especially the evacuees in the first level might have to evacuate several times. So, we assume that the seven impact levels are classified into three impact levels, it implies that we have three evacuation periods. Based on historical data, we can assume that the probability of three impact levels is 0.73, 0.25, and 0.02, respectively[26)] as shown in Table 4.2. In this study, we consider 123 communities and 43 candidate shelters, as shown in Figure 4.7. Unlike other evacuation, the evacuee's behavior during flood disaster is uncertain, someone needs to evacuate after they hear alarm immediately, but someone needs to evacuate when the disaster strike. Hence, evacuee's behavior should be determined. The proportion of the population that needs to evacuate in each evacuation period is referred from Lauthep et al., 44.81% evacuate immediately after warning signal given by the local government, 8.00% evacuate when the flood level is lower than 0.5 meter, and 4.44% evacuate when the flood level is over than 0.5 meters[27)]. Not that the remaining percentage is the people who do not need to evacuate. Finally, the maximum limit of selected shelter is assumed as 25 shelters and the utilization of shelter must greater than or equal to 80%.

Table 4.2 Classification of level for hierarchical evacuation model

Impact level and evacuation period	1	2	3
Probability	0.73	0.25	0.02
Ping river at P.1 (m)	3.7-4.1	4.1-4.6	Over 4.6
No. affected communities	18	47	123

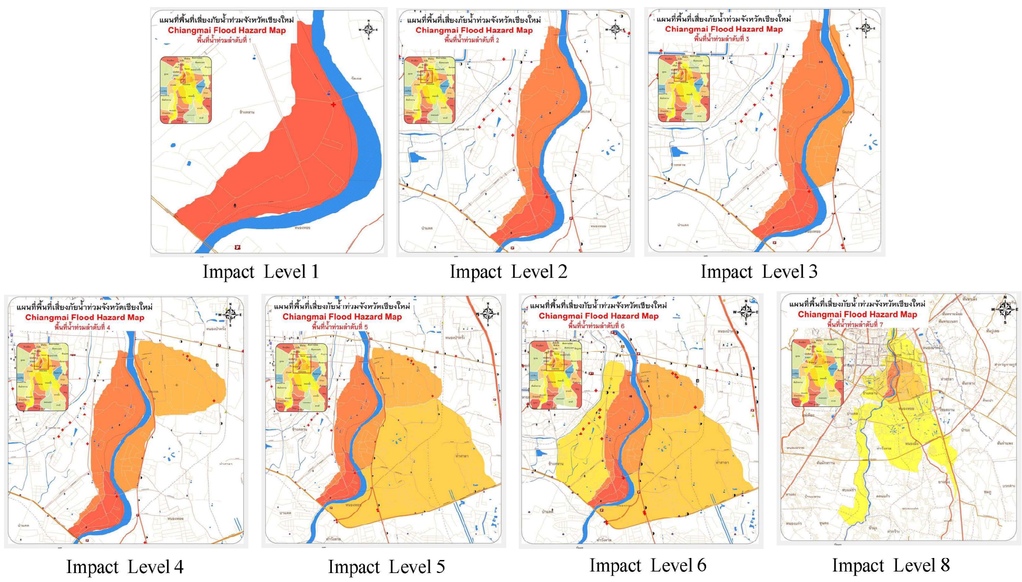


Figure 4.6 Seven impact levels of the Chiang Mai flood hazard map [25]

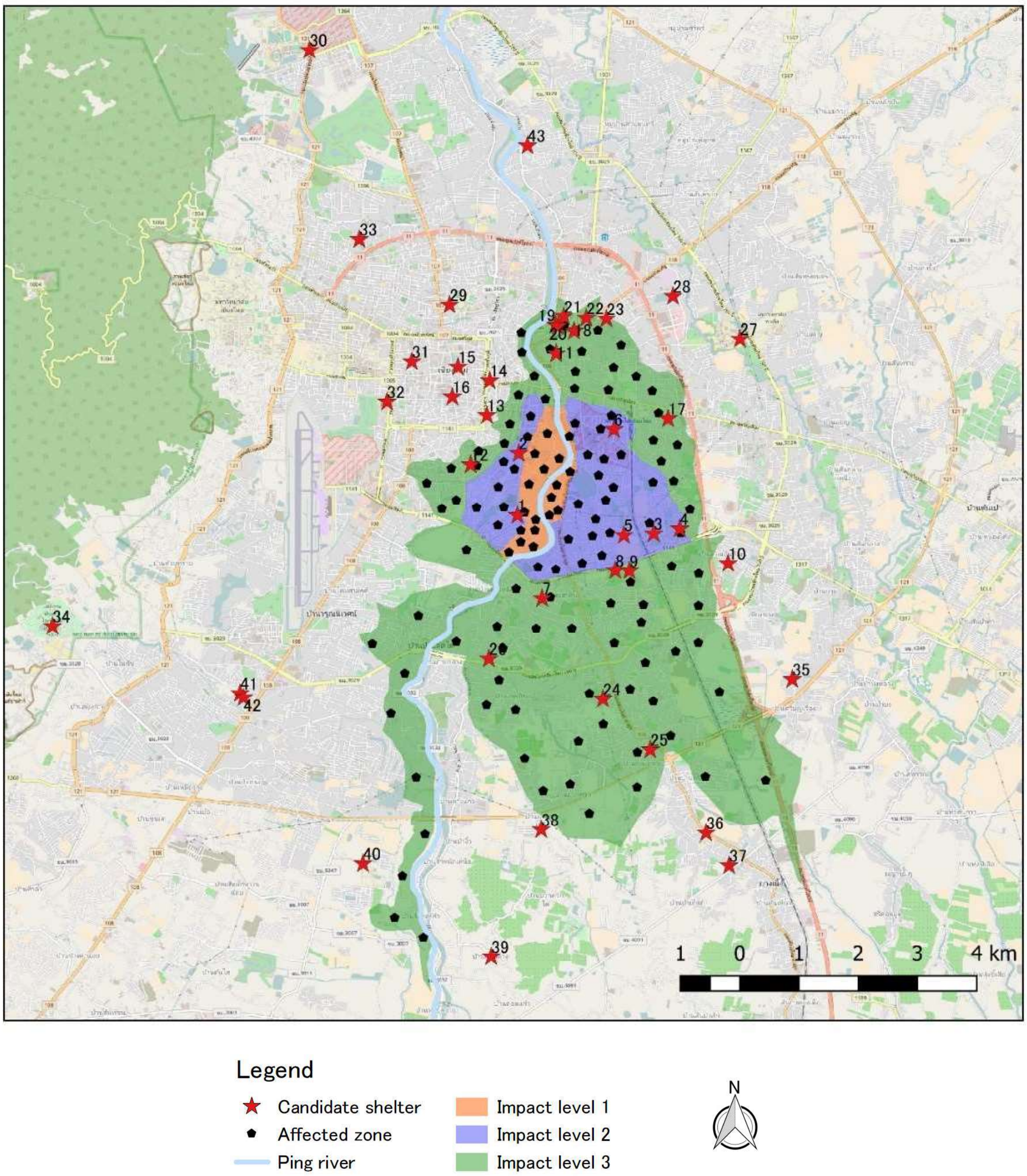


Figure 4.7 Geographical location of three impact level areas, candidate shelters, and affected communities in Chiang Mai, Thailand

4.5 Computational results

We solved the proposed mathematical model using the Gurobi Optimizer Ver. 6.0.0 mathematical programming solution software. All experiments were run on a personal computer with an Intel (R) Core (TM) i7-6700 CPU (3.40GHz) and 16 GB of RAM.

4.5.1 Results

After we code and solve the mathematical model into optimization solver software. Figure 4.8 shows the scheme of evacuation planning and flood shelter site location. According to the formulated system, the total expected population-weighted travel distance is 5,729,246. Among the 43 candidate shelters, 24 were identified as shelters that operate at their capacity to serve the communities during flood disaster occurrence. In the first evacuation period needs at least 4 shelters for supporting evacuees in which shelter 1, 2, 7 and 11 are selected, while the total expected population-weighted travel distance in this evacuation period is 1,695,470. The selected shelter of the second evacuation period consists of shelter 7-9, 11-14, and 17. The total expected population-weighted travel distance of the second evacuation period is 2,810,010. For selected shelter of the third evacuation period, there are shelter 10, 13-16, 27-29, 31-32, 35-38, 40 and 42, while the total expected population-weighted travel distance is 1,223,770.

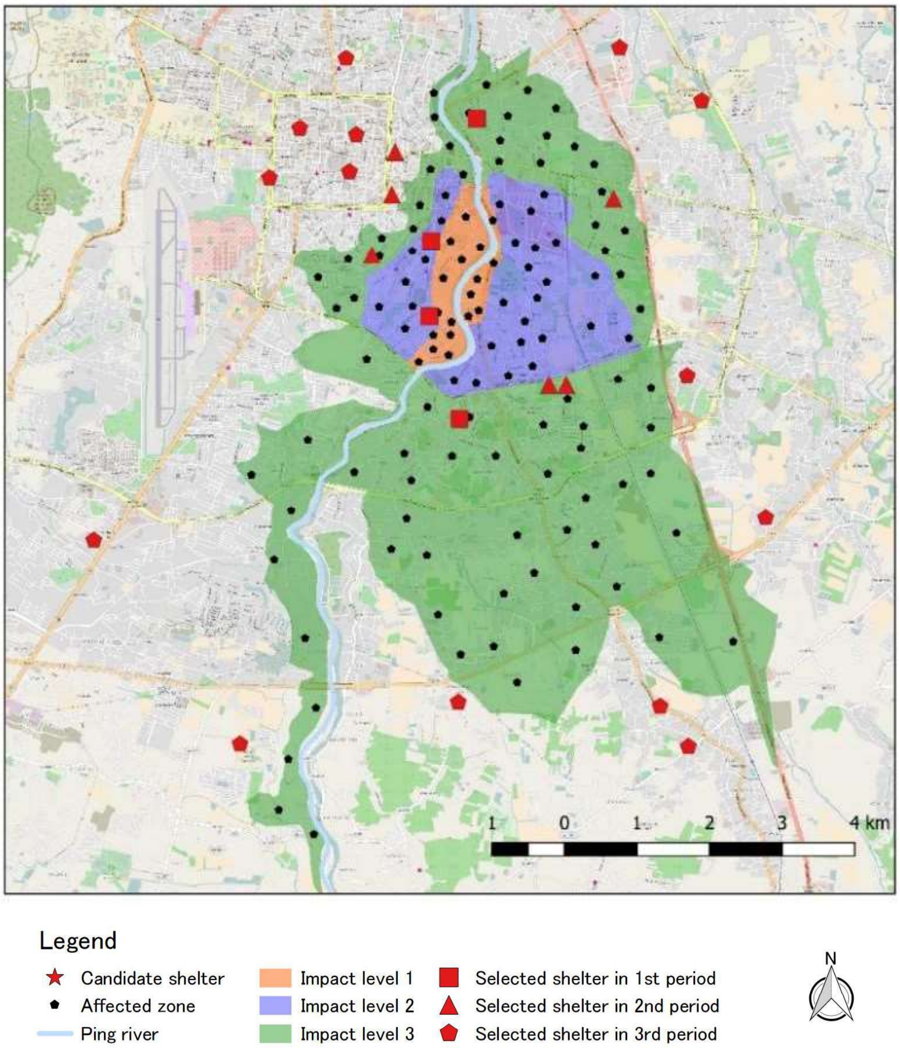


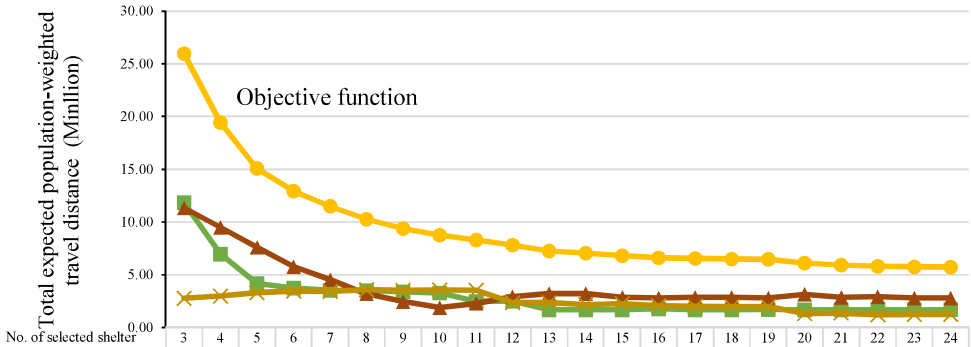
Figure 4.8 The scheme of flood-shelter location and evacuation planning under hierarchical evacuation concept

Following the conceptual model, the solution of this formulated system is able to describe that if the flood warning system alarms for the 1st evacuation, the square symbol is opened for supporting evacuees in the 1st impact level zone (Orange zone), in which there are shelter 1, 2, 7 and 11. In the case of expansion of flood zones to the second zone, the 2nd evacuation period will be started. The triangle symbol is opened for supposing evacuees in both the 1st impact level (Orange zone) and the 2nd impact level (Violet zone) that consists of the shelter 8-9, 12-14, and 17. While the selected shelters in the 1st evacuation period where locate out of impact zone are still used for supporting evacuees, there are shelter 7 and 11. Finally, in the case of huge flooding, the shelter 10, 15-16, 27-29, 31-32, 35-38, 40 and 42 are opened (Pentagon symbol) and the shelter 13 and 14 (Triangle symbol) are still opened for supporting evacuees of three hazard areas. The decision makers can plan to follow hierarchical evacuation model. However, some evacuation periods can be skipped over, in which it depends on the decision of decision makers and situation. Note that the selected shelters in previous evacuation period where to locate in next impact level zone are closed. The evacuees in those shelters are evacuated to new shelters. For example, in 2nd evacuation period, the selected shelters (Triangle symbol) in 1st evacuation period that locate in impact level 2 will be closed (Shelter No. 1 and 2).

4.5.2 Sensitivity analysis

In this section, we present a sensitivity analysis to show how the parameters affect the results with respect to changing input parameters. The total number of selected shelter constraint is a major constraint that impinging on both shelter site selection and evacuation planning. The total number of shelter constraint was varied from 24 shelters to 3 shelters, in decrements of 1, to represent the different total number of the shelter with aspect to an objective function as shown in Figure 4.9. Moreover, we also represent the derived total number of selected shelter in each evacuation period under the different total number of selected shelter as shown in Figure 4.10. Both of the figures show the result when the model is run multiple time with varying the total number of selected shelter. The graph presents not only the total expect population-weighted travel distance but also and the total expect population-weighted travel distance in each evacuation period. The result found that when the total number of selected shelter is decreased, the total expected population-weighted travel distance is continually increased. At first glance, the gradual increase in the maximum number of selected shelter appears to reduce the total expected population-weighted travel distance. However, when we provide less number of selected shelter, it will threat to the total expected population-weighted travel distance, it may make likely that evacuee will be forced to endure a longer transfer distance. Especially, when we set the number of selected shelter less than 10, the total expected population-weighted travel distance is rapidly increased. According to this sample data set, the formulated system is unable to aid all affected communities if the number of selected shelter is less than 3. The objective function, on the other hand, is unchanged when the maximum total number of selected shelter has more than 24 shelters according to the same performance of each response result. According to the bound of the number of selected shelter is decreased with its decrements, some shelters are removed from the previous list in which shelter selection depends on its significance.

According to the first evacuation period is significant to objective function because the probability of flooding this period is the highest, so the system attempts to make the shortest distance in this period that affects to shelter site selection. In the first evacuation period, the expected population-weighted travel distance is constant over time during the total number of selected shelter as 22-24. After that, it is slightly increased. The trend of this evacuation period exhibits similar trends as the objective function. The total number of selected shelter in this evacuation period is selected between 2-5 shelters. In the second evacuation period, the expected population-weighted travel distance is higher than the first evacuation period although the probability of this evacuation period is less than the first evacuation period because the shelters are located farther from affect zone and the number of community is also increased. However, when the total number of selected shelter is set at 6-9 shelters, the expected population-weighted travel distance is less than the first evacuation period. The maximum of the number



No. of selected shelter	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
The objective function	25.96	19.42	15.07	12.94	11.50	10.26	9.39	8.74	8.29	7.80	7.26	7.06	6.79	6.61	6.54	6.51	6.48	6.12	5.90	5.80	5.74	5.73
The 1st evacuation period	11.83	6.95	4.18	3.75	3.54	3.49	3.39	3.29	2.46	2.51	1.67	1.67	1.67	1.75	1.67	1.67	1.70	1.67	1.67	1.70	1.70	1.70
The 2nd evacuation period	11.36	9.50	7.59	5.76	4.53	3.18	2.47	1.89	2.29	2.92	3.23	3.23	2.87	2.80	2.87	2.87	2.81	3.13	2.87	2.91	2.82	2.81
The 3rd evacuation period	2.78	2.97	3.29	3.44	3.43	3.59	3.54	3.56	3.54	2.36	2.36	2.16	2.25	2.06	2.00	1.96	1.98	1.31	1.36	1.19	1.23	1.22

Figure 4.9 The derived total expected population-weighted travel distance under the different total number of selected shelter

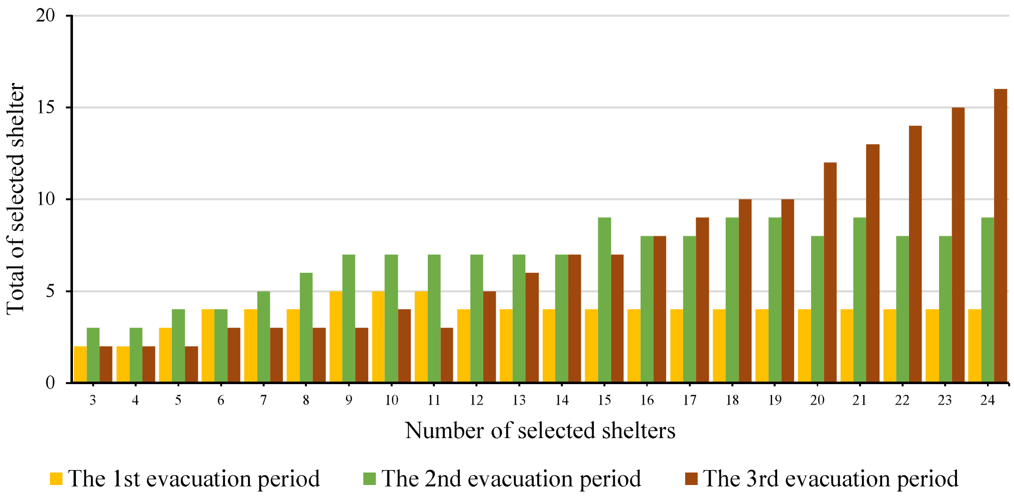


Figure 4.10 The derived total number of selected shelter in each evacuation period under the different total number of selected shelter

of shelters in this period requires 9 shelters for minimum the expected population-weighted travel distance, while this evacuation period needs at least 3 shelters for covering all demands. For the third evacuation period, the trend is gradually changed because this evacuation period has the least probability of flood occurrence. The expected population-weighted travel distance in this period is slightly increased when the number of selected shelter is decreased. The number of selected shelter in this evacuation period need at least 16 shelters when the selected shelter limit is provided at 24 shelters. On the other hand, the number of selected shelter in this evacuation period need at least 2 shelters when the selected shelter limit is provided at the minimum total number of selected shelter.

Controls the utilization of selected shelter areas is one constraint that can impact the formulated system. We presented the derived total expected population-weighted travel distance and the derived total number of selected shelter under the different value for utilization of selected shelter areas, as shown in Figure 4.11 and 4.12. Moreover, Figure 4.11 and 4.12 also present the result of the unlimited number of shelter site selection. The value for utilization of selected shelter areas was varied from 0 to 1, in increments of 0.1. From Figure 4.11 and 4.12, we see that the best objective value of both solutions is reached at the minimum value for utilization of selected shelter areas. If we increase this value with its increments, the objective function (Z1) is exponentially increased. The objective value of the limited number of shelter site selection is higher than the objective value of the unlimited number of shelter site selection during the value for utilization of selected shelter is set at 0-0.5. However, during 0.6-0.9, the objective value has the same result, including the number of selected shelter. In the limited number of shelter site selection, the total expected population-weighted travel distance is stable as approximately 5.544 million during the value for utilization of selected shelter areas is set at 0-0.4. Then, the trend of the objective function is increased step by step. On the other hand, the total number of selected shelter is decreased when the value for utilization of selected shelter areas is increased. During the value for utilization of selected shelter is set at 0-0.5, the total number of selected shelter is stable about 25 shelters. Then, it drops to 24 and 23, respectively. For the unlimited number of shelter site selection, the total expected population-weighted travel distance is started with 5.527 million, while this formulated system needs to open 29 shelters. The objective value is then continually increased while the total number of selected shelter is simultaneously decreased. The both formulated system end at 0.9 for the relief response to be feasible. From the result of Figure 4.11 and 4.12, it implies that the value for utilization of selected shelter is impinging on the travel distance of evacuee. If the government or policy makers provide too much the value for utilization of selected shelter, it may make likely that evacuee will be forced to endure a longer transfer distance. On the other hand, if the government or policy makers provide too few the value for utilization of selected shelter, it may make likely that the government has to open more shelter in which the government has to support more finance for establishing shelters.

Furthermore, we present the fluctuation of the expected population-weighted travel distance under the different situation of the probability of flooding. This is one of the criteria that can threaten to the objective function. We conducted computational experiments to illustrate how the case study varies when the situation of the probability of flooding is changed. We proposed three scenarios for testing case study in which the probability in each experiment is shown in Table 4.2. In the scenario 1, the probability of the impact level 1 is the highest chance of flooding while the impact level 2 and 3 are low chance of flooding. In the scenario 2, the probability of the impact level 1 and 2 is the biggest proportion to occur flooding except for the impact level 3. Finally, in the scenario 3, all impact levels are the same proportion of flooding chance. Moreover, the probability value of each impact level of a case study that proposed in section 4.5.1 is also represented in the last row of Table 4.3.

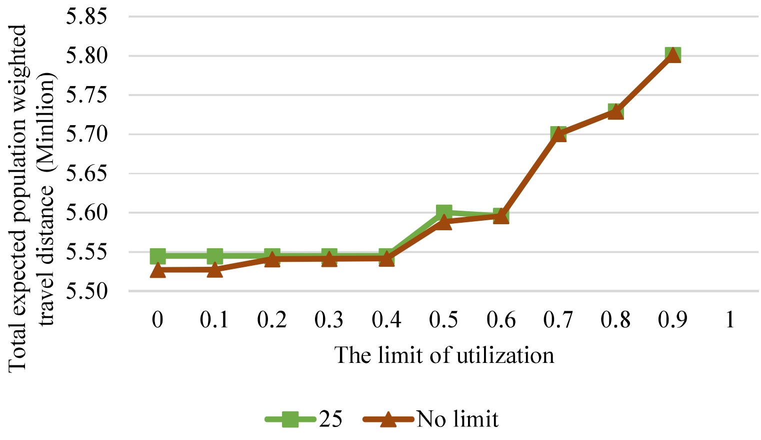


Figure 4.11 The derived total expected population-weighted travel distance under the different utilization of selected shelter areas

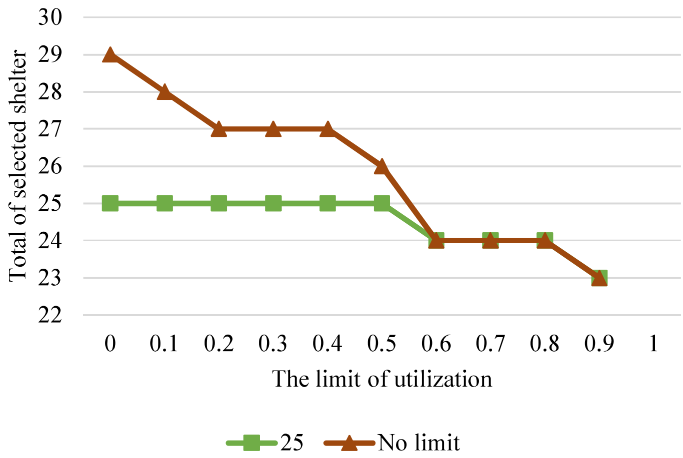


Figure 4.12 The derived total number of selected shelter under the different utilization of selected shelter areas

Table 4.3 The computational experiments of the probability of flood occurrence

Scenario	Impact level 1	Impact level 2	Impact level 3
1	0.90	0.09	0.01
2	0.49	0.49	0.02
3	0.33	0.33	0.33
Case study	0.73	0.25	0.02

Three computational experiments are run and showed the result in Figure 4.13. The three schemes of flood evacuation planning and shelter site selection under the different scenarios are shown in Figure 4.14. We can see that the scenario 1 is quite same the case study in which the shelters located in impact level 2, 3 and non-impact area and the evacuation planning is generated under hierarchical evacuation concept. The objective function is 3.669 million while the total number of selected shelter is 23 shelters. The three shelters (Square symbol) are opened for the first evacuation period. Then, the eight shelters (Triangle symbol) are opened for the second evacuation period in case of extension of flood zone to the second zone (Violet zone). While the shelters that locate out of impact level 2 is still used for supporting evacuees. Finally, if the expensive flood will occur, twelve shelters (Pentagon symbol) is opened for supporting evacuees of three hazard zones including to two shelters (Triangle symbol) that locate out of impact level 3 zone (Green zone). In the scenario 2, the selected shelters are only located in impact level 3 and the non-impact area. The objective is 7.125 million while the total number of selected shelter is 22 shelters. In this case, the six shelters (Square symbol) are proposed to open for the first evacuation period. Then, the two shelters (Triangle symbol) are selected to open for the second evacuation period, while the selected shelters in the first evacuation period are still used for supporting the second evacuation period as well. Finally, in the case of biggest flooding, the fourteen shelters (Pentagon symbol) are selected including to the selected shelters in previous evacuation periods that locate out of the affected zone. For the scenario 3, all selected shelters are established in the non-impact area. In this case, it seems that this plan is no hierarchical evacuation planning. However, the evacuation planning will evacuate three times that starts with impact level zone 1, 2, 3, respectively. The square symbol is firstly opened, then following with triangle symbol and pentagon symbol, respectively. The objective value in this plan is the highest to estimate to be 22.601 million, while the total number of selected shelter is 16 shelters.

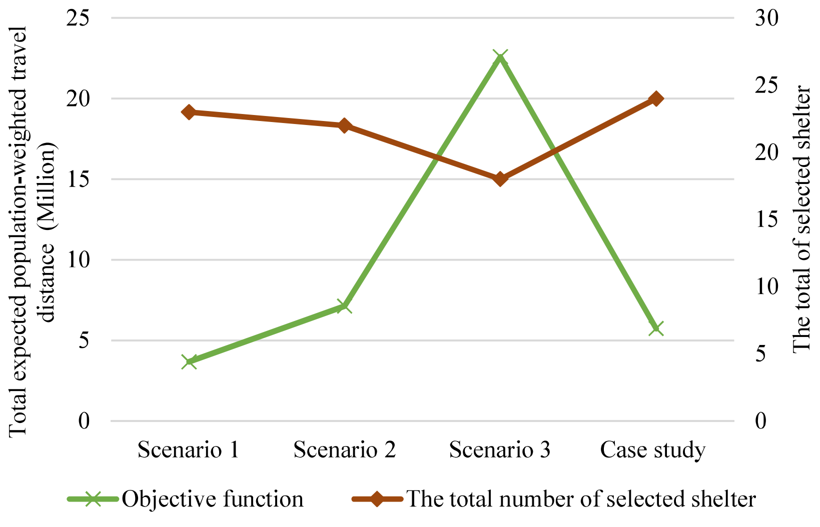


Figure 4.13 The derived objective function and total number of selected shelter under the different scenarios

According to the result of the derived expected population-weighted travel distance under the different situation of probability of flooding, we found that if the impact level 1 is a large proportion for probability of flooding, the first evacuation period is the most important in which the nearby shelters are selected because the objective function aims to make the minimum expected population-weighted travel distance in this evacuation period. On the other hand, when all impact level has same proportion for the probability of flooding, the objective function aims to make the short distance in all evacuation period.

To recommend for decision making's government in the future, if they use the expected probability based on historical data by CENDRU, they should select the proposed evacuation planning for this case study that shows in Figure 4.8. If government expect that the severity of flood disasters will be reduced in the future by improving or controlling the Ping river, they can use the scenario 1. On the other hand, if government expect that the severity of flood disasters will increase in the future, they should select the scenario 2 or 3 for flood evacuation planning and shelter site selection. However, the government or policy-makers should be interested in the number of open shelters and the utilization of shelter because it represents the efficient flood evacuation planning including financial and evacuation distance[23)]. Finally, the final point depends on policy maker's preference.

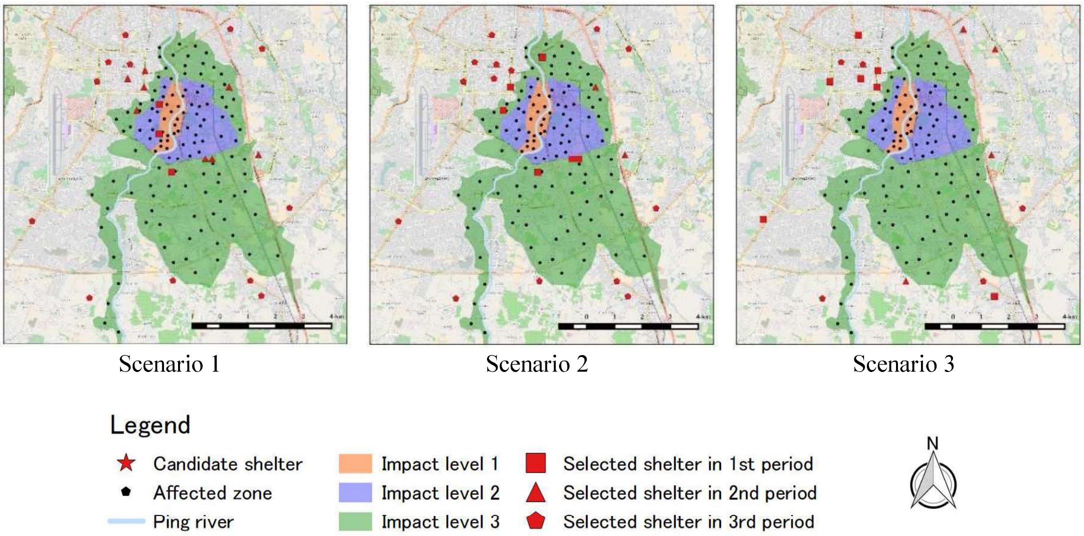


Figure 4.14 The three schemes of flood evacuation planning and shelter site selection under the different scenarios

4.5.3 Advantage of proposed conceptual model

Our conceptual model can serve emergency management purposes. The first is to help in preparation stage including spatial distribution of shelter under uncertainty of flood occurrences. The second is to aid in response stage in order to provide evacuation flow and directions at each evacuation period. The third is to help in recovery stage for reentry process in term of distance [26]. Our conceptual model also considers utilization of shelter, capacity restriction of shelter and evacuee's behavior that reflect the real problem constraints. Furthermore, when the flood disaster occurs with low-impact events, the evacuees do not need to evacuate to the shelter with a longer transfer distance and the local government can reduce the budget as well. Although this evacuation planning is designed based on hierarchical evacuation planning, it is not necessary to evacuate following the step of the plan. If the local government can predict that the severity of flooding will occur with the expensive flood, the local government can skip over the first or the second evacuation period to the next evacuation period in which this depends on the decision making's local government.

4.5.4 Current problem – to – solution findings

As stated earlier, this case study is faced with flood disaster almost every year. However, in the reality of this problem, many times there are errors and inefficient performance issues including unsuitable opened shelter site, inadequate capacity of shelter, long distance evacuation in perspective of evacuee and amiss assignment.

In this study, we determined that our proposed conceptual model could overcome those happenable problems. Moreover, this could consider the behavior of evacuees during the evacuation, utilization of selected shelter area, and the uncertain situation of flooding, simultaneously. To compare the performance with previous evacuation plan of the case study, in which the local government always select shelter No. 30 and No. 34 for supporting evacuees whenever flooding, our model can reduce the expected population-weighted travel distance to estimate be 80% with respect to the formulated system and can cover all of the demand points in each affected zone. Note that the binary of the other shelters is set as 0 except shelter No. 30 and 34 in the system. Although this can reduce the travel distance of evacuation, this is faced with risk problem of open shelter at potential flooding area, the assignment of this rather complicates due to the behavior of evacuees and some communities might have to evacuate several times. However, this proposed system can apply with the real-world case and respond to evacuee's behavior and uncertain situation of flooding as well.

To improve preparedness, the government should provide more efficient forecast. This proposed model should consider in road closures or traffic congestion, a difference of travel speed depending on the mode selection, accessibility of shelter site, financial cost [28] and risk of open shelter at potential flooding area. Besides, this should consider how to classify evacuation period in which it could affect to the effectiveness of evacuation as well.

4.6 Conclusions

This study presented a stochastic linear mixed-integer programming mathematical model for flood evacuation planning to optimize decision related to shelter site selection under hierarchical evacuation planning. The proposed mathematical model considers minimum expected population-weighted travel distance as the objective function. This study not only provides a flood shelter but also determines hierarchical evacuation concept, distribution of shelter, utilization of shelter, capacity restrictions of shelter and evacuee's behavior for flood disaster that balances the preparedness and risk despite the uncertainties of flood events. Our proposed model was validated by generating a base case scenario using real data for Chiang Mai province, Thailand. Besides, we also proposed sensitivity analysis for more guideline under uncertainty decision. This study will be great significance in helping policymakers consider both spatial and performant aspect of the strategic placement of flood shelters and evacuation planning under uncertainties of flood scenario.

The implementation of the proposed mathematical model also has limitations. According to unlike another natural disaster, it cannot be generated to others disaster due to some condition of each natural disaster are different such as shelter type, time condition, etc. However, our mathematical model can apply to any other city in flood situation as well. Although this proposed conceptual model is quite complicated, it can respond to many criteria completely. Consequently, the policymaker should decide carefully to apply with a real case. To reduce a complexity, the affected communities should not be separated too many because it will be difficult for evacuation management. In future research, the proposed model should consider in road closures or traffic congestion, road network, a difference of travel speed depending on the mode selection and accessibility of shelter site that may affect to an efficient evacuation. Furthermore, this model should consider financial cost and risk of open shelter at potential flooding area as well.

Acknowledgment: We sincerely thank The Natural Disaster Research Unit of Civil Engineering Department of Chiang Mai University (CENDRU) for supporting the data.

4.7 References

[1] Guha-Sapir, D., Hoyois, P., & Below, R. (2015). Annual Disaster Statistical Review 2014, The Numbers and Trends, Brussels, CRED.

[2] Xu, J., Wang, Z., Shen, F., Ouyang, C., & Tu, Y. (2016). Natural disasters and social conflict: A systematic literature review. International journal of disaster risk reduction, 17, 38-48. World Health Organization (WHO), [Online]. Available: http://www.who.int/hac/about/definitions/en/ [Accessed 13 July 2016].

[3] Jabbarzadeh, A., Fahimnia, B., & Seuring, S. (2014). Dynamic supply chain network design for the supply of blood in disasters: a robust model with real world application. Transportation Research Part E: Logistics and Transportation Review, 70, 225-244.

[4] Boonmee, C., Asada, T., & Arimura, M. (2017). Improving evacuation planning and shelter site selection for flood disaster: A stochastic approve, In Proceedings of 54th Infrastructure Planning in Japan Society of Civil Engineers, CD-ROM, pp. 2313-2321.

[5] Caunhye, A. M., Nie, X., & Pokharel, S. (2012). Optimization models in emergency logistics: A literature review. Socio-economic planning sciences, 46(1), 4-13.

[6] Özdamar, L., & Ertem, M. A. (2015). Models, solutions and enabling technologies in humanitarian logistics. European Journal of Operational Research, 244(1), 55-65.

[7] Boonmee, C., Arimura, M., & Asada, T. (2017). Facility Location Optimization Model for Emergency Humanitarian Logistics. International Journal of Disaster Risk Reduction. Vol. 24, 485-498.

[8] Zheng, Y. J., Chen, S. Y., & Ling, H. F. (2015). Evolutionary optimization for disaster relief operations: a survey. Applied Soft Computing, 27, 553-566.

[9] Chanta, S., & Sangsawang, O. (2012). Shelter-site selection during flood disaster. Lect. Notes Manag. Sci, 4, 282-288.

[10] Boonmee, C., Ikutomi, N., Asada, T., & Arimura, M. : Multi-model optimization for shelter-site selection: A case study in Banta Municipality, Thailand, In Proceedings of 53rd Infrastructure Planning in Japan Society of Civil Engineers, CD-ROM, pp. 2175-2181.

[11] Chowdhury, J. U., Watkins, D. W., Rahman, M. R., & Karim, M. F. (1998). Models for cyclone shelter planning in Bangladesh. Water international, 23(3), 155-163.

[12] Santos, M. G., Meriño, M., Sore, N., & Quevedo, V. C. (2013, December). Flood Facility

Location-Allocation in Marikina City Using MCLP with Lagrange. In The 14th Asia Pacific Industrial Engineering and Management Systems Conference, Philippines, December (pp. 3-6).
[13] Wang, K., Chen, N., Tong, D., Wang, K., Wang, W., & Gong, J. (2016). Optimizing precipitation station location: a case study of the Jinsha River Basin. International Journal of Geographical Information Science, 30(6), 1207-1227.
[14] Kulshrestha, A., Wu, D., Lou, Y., & Yin, Y. (2011). Robust shelter locations for evacuation planning with demand uncertainty. Journal of Transportation Safety & Security, 3(4), 272-288.
[15] Kongsomsaksakul, S., Yang, C., & Chen, A. (2005). Shelter location-allocation model for flood evacuation planning. Journal of the Eastern Asia Society for Transportation Studies, 6, 4237-4252.
[16] Li, A. C., Nozick, L., Xu, N., & Davidson, R. (2012). Shelter location and transportation planning under hurricane conditions. Transportation Research Part E: Logistics and Transportation Review, 48(4), 715-729.
[17] Liu, Y., Lai, X., & Chang, G. L. (2006). Two-level integrated optimization system for planning of emergency evacuation. Journal of transportation Engineering, 132(10), 800-807.
[18] Feng, C. M., & Wen, C. C. (2005). A bi-level programming model for allocating private and emergency vehicle flows in seismic disaster areas. In Proceedings of the Eastern Asia Society for Transportation Studies, Vol 5 (Vol. 5, pp. 1408-1423).
[19] Salman, F. S., & Yücel, E. (2015). Emergency facility location under random network damage: Insights from the Istanbul case. Computers & Operations Research, 62, 266-281.
[20] Mirzapour, S. A., Wong, K. Y., & Govindan, K. (2013). A capacitated location-allocation model for flood disaster service operations with border crossing passages and probabilistic demand locations. Mathematical Problems in Engineering, 2013.
[21] Chen, Z., Chen, X., Li, Q., & Chen, J. (2013). The temporal hierarchy of shelters: a hierarchical location model for earthquake-shelter planning. International Journal of Geographical Information Science, 27(8), 1612-1630.
[22] Hu, Z. H., Sheu, J. B., & Xiao, L. (2014). Post-disaster evacuation and temporary resettlement considering panic and panic spread. Transportation research part B: methodological, 69, 112-132.
[23] Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. Operations research, 19(6), 1363-1373.
[24] Civil Engineering Chiang Mai University Natural Disaster Research Unit' CENDRU, Chiang Mai City Flood Preparedness System, [Online]. Available: http://cendru.eng.cmu. ac.th/cmflood/map.html. Accessed 13 July 2016.
[25] Manopiniwes, W., & Irohara, T. (2017). Stochastic optimisation model for integrated decisions on relief supply chains: preparedness for disaster response. International Journal of Production Research, 55(4), 979-996.
[26] LUATHEP, P., SUWANSUNTHON, A., SUTTHIPHAN, S., & TANEERANANON, P. (2013). Flood evacuation behavior analysis in urban areas. Journal of the Eastern Asia Society for Transportation Studies, 10, 178-195.
[27] Boonmee, C., Takumi, A., & Mikiharu, A. (2018). A bi-criteria optimization model for hierarchical evacuation and shelter site selection under uncertainty of flood events. Journal of the Eastern Asia Society for Transportation Studies, 12(2017), 251-268.

Chapter 5

A Bi-Criteria Optimization Model for Hierarchical Evacuation and Shelter Site Selection under Uncertainty of Flood Events

5.1 Introduction

Since the 1950s, the number and magnitude of disasters have been continuously increasing. According to annual disaster statistical review 2014 [1], 324 persons were stricken by natural disaster and economic system was damaged as approximately US$ 99.2 billion. According to the International Disaster Database, Asia and the Americas have been the continents most affected by disasters. Because of the increasing severity of recent disasters, many academicians have paid a great deal of attention to “Disaster management (DM)” for the purposes of helping at-risk persons to avoid or recover from the effect of the disaster. Disaster situations can be divided into two stages: a pre-disaster (mitigation and preparation) stage and a post-disaster (response and recovery) stage [2].

Flood disaster is largest share in natural disaster occurrence in 2014 as approximately 47.2%. The number of floods and mass movement of hydrological origin were 153 disasters in 2014 that caused 42.3 million victims or 30% of total disaster victims with economic damaged around US$ 37.4 billion. The biggest flood disaster had been occurred in China in 2007 and 2011, more than 100 million people were hit. Furthermore, the most expensive flood had been occurred in Thailand in 2011, with economic damages estimated to be US$ 42.1 billion. During flood situation, people in an affected zone have to decide where to evacuate to safety. The shelter is a public safe place provided and organized by the government in order to support people in an affected area. Thus, preparedness design is a major stage to design planning of activities to follow in case the flood disaster situation. In flood shelter site selection and flood evacuation planning, there are many major criteria that should be considered such as uncertainty of occurrence, evacuee’s behavior, planning budget and hazard of flood disaster [3]. Besides, an effective planning strategy in response to flood disaster must take into account a short travel distance [4]. As pointed out by several studies, existing optimization model in this field lack a determined perspective for uncertainties of flood events, evacuation’ behavior and hierarchical evacuation model. Therefore, we aim to develop new evacuation planning for overcoming this challenge, in which we consider such a problem in our study.

This chapter aims to propose a stochastic linear mixed-integer programming model for flood evacuation planning to optimize decision related to shelter site selection under a hierarchical evacuation concept. This study is applied to probabilistic scenarios that reflect the uncertainty of flood events and their consequences. To develop an effective flood evacuation model, the objective function in this study considers not only in terms of response distance but also in terms of risk index of shelter, simultaneously. Furthermore, our model scrutinizes evacuee’s behavior and financial constraint as well.

The remainder of this chapter is organized as follows: Section 5.2 presents a review of related literature. Section 5.3 shows conceptual model, proposed mathematical model and solution approach. To show the usefulness of the proposed model, a case study of Thailand is shown in section 5.4. Section 5.5 shows the computational results and discussion of the case study. Finally, the conclusion and future research are presented in section 5.6.

5.2 Literature reviews

This section presents an overview of relevant literature. There are many papers dealing with sheltering operation and evacuation planning. Santos *et al.* [5] proposed flood facility location-allocation in Marikana city by using maximal covering location problems (MCLP) with Lagrange optimization model. This study aimed to optimize the number of shelters by relaxing constraints in order to obtain the optimal demand coverage for every facility location and also considered flood level constraint. Similarly, Wang *et al.* [6] proposed an MCLP-based optimization model, precipitation station MCLP, to site precipitation stations. The proposed model considered the terrain condition, the characteristic if a rainfall network, and the associated rainfall monitoring demand. In a related study, Chanta and Sungsawang [7] proposed bi-objective optimization model to select appropriate temporary shelter sites for flood disaster in Bangkruai, Thailand. The proposed model aims to maximize the number of victims that can be covered within a fixed distance and to minimize the total distance of all victims to their closest shelters by using epsilon constraint approach. Boonmee *et al.* [8] proposed multi-model optimization for selecting shelter site and evacuation planning, four mathematical models were formulated under a dynamic of both constraint and model type. In each model, the objective function is to minimize the total travel distance. Furthermore, Kongsomsaksakul *et al.* [9] presented optimal shelter location for flood evacuation planning, bi-level programming model was formulated. Others bi-level programming model was proposed by Feng and Wen [10] for managing the emergency vehicle and controlling the private vehicle flows in earthquake disaster. They considered a multi-community, two-model network flow problem base on the concept of bi-level programming and network optimization theory.

Several researchers have considered on shelter site selection and evacuation planning based on a stochastic approach for dealing with uncertainty. Mirzapour *et al.* [11] presented mixed integer nonlinear programming model of a capacitated facility location-allocation problem which simultaneously considers the probabilistic distribution of demand locations and a fixed line barrier in a region. Moreover, Salmam and Yücel [12] proposed a stochastic integer programming model for determining the location of emergency response facilities in the pre-disaster stage. This research aims to maximize the expected total demand covered within a predetermined distance parameter, over all possible network realizations. For the integrated decision on shelter site selection and evacuation planning under hierarchical location concept, Chen *et al.* [13] proposed a three-level hierarchical location model to optimize the location of earthquake-shelter by taking into account this temporal variance. This proposed model not only considers changing needs of refugees but also determines financial constraints imposed upon the construction of shelters. Another multi-step evacuation was proposed by Hu *et al.* [14]. This chapter aims to present a post-disaster evacuation and temporary resettlement considering panic and panic spread. The proposed mixed-integer linear programming model was constructed for multi-step evacuation and temporary resettlement by minimizing the panic-induced psychological penalty cost, psychological intervention cost, transportation cost, and building shelter cost. According to previous studies have considered all flood shelters and flood evacuation planning to be the same; however, this assumption disregards uncertainty of flood events and evacuee’s behavior. Moreover, the related existing literature in flood disaster management, there is no research considering flood shelter site selection and flood evacuation planning under hierarchical evacuation concept as far as we know. As above-mention problems are scarce, we proposed such a problem in our study.

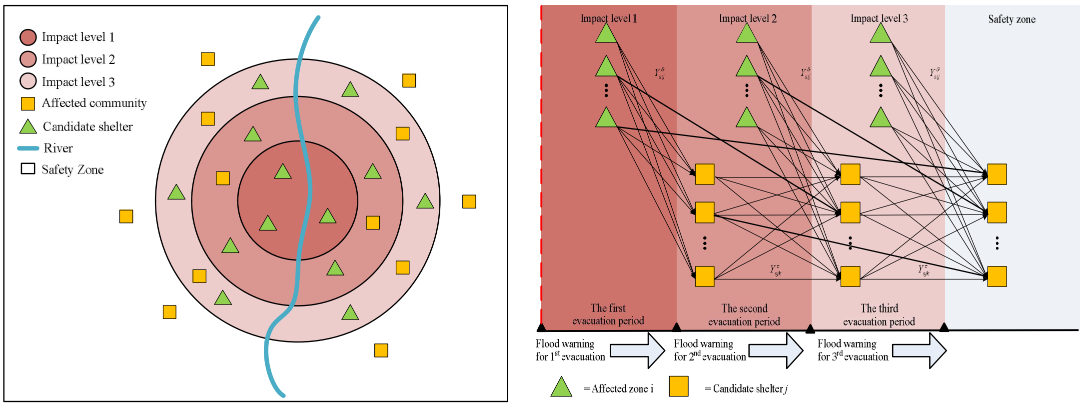
5.3 Stochastic linear mixed-integer programming model

This section discusses a bi-criteria programming model for shelter site selection and evacuation planning during floods under a hierarchical evacuation model. The conceptual model, mathematical model, and solution technique are described as follows:

5.3.1 Conceptual model and assumptions

In this study, the flood shelter site selection and flood evacuation planning are designed under hierarchical evacuation concept in which each evacuation step is called "Evacuation period". The evacuation periods are provided by the decision makers or local government that can be separated with respect to the step of impact level or step of flooding from hazard map. For instance, in Figure 5.1., we represent three-level hierarchical evacuation model that consists of three evacuation periods and three impact levels. In the 1st evacuation period, when the flood warning system alarms for the 1st evacuation, the refugees who stay in impact level 1 will be assigned to one of the nearby shelters. In the 2nd evacuation period, when the flood warning system alarms for the 2nd evacuation, the refugees who stay in impact level 2 will be assigned to the nearby shelters. While the refugees of selected shelters in the 1st evacuation period where locate in impact level 2, they will be relocated to new shelters. In the 3rd evacuation period, when the flood warning system alarms for the 3rd evacuation, the refugees who stay in impact level 3 will be evacuated to one of the nearby shelters. While the refugees of selected shelters in the 1st evacuation period and the 2nd evacuation period where locate in impact level 3, they will be relocated to the new shelters as well. Before the mathematical model is considered, we make the following assumptions on the problem:

1. According to evacuee's behavior during flood events, some refugees always evacuate neither before the disaster or after the disaster [15]. So, we assume that the refugees can evacuate to shelter any evacuation periods under varying needs of the refugees.
2. The affected community can be served by one shelter in each period.
3. Some shelter can be located in flooding risk area.
4. The weight associated with each demand point is not considered in the objective function.
5. Shelters have a limited capacity for accommodating the demand assigned to them.
6. An occurrence of a disaster and an occurrence of an evacuation order are mixed up in this study, in which the evacuation period is defined as following the occurrence of a disaster or impact level with respect to the perspective of decision makers.



(a) (b)

Figure. 5.1 The conceptual model of flood shelter site selection and flood evacuation planning under hierarchical evacuation model; hazard map of framework (a) and conceptual model (b).

5.3.2 The Mathematical Formulation

Most evacuation models measure the efficiency of evacuation by total travel cost in terms of response distance or time [4]. According to the floods typically are known about several hours before communities will be affected, evacuees will have sufficient time for evacuation. Thus, the first objective function aims to focus on travel distance criterion. Base on assumption of the conceptual model, some shelters can be located in the flooding risk area. Therefore, the second objective function is to concentrate on risk index of shelter criterion. Note that the risk index of shelter indicates possibility of flooding at the shelter that relates to probability of flooding (discusses in section 4). This proposed model considers that related to probabilistic scenarios due to the uncertainty that surrounds disasters and their consequences. A flood hazard map is used to generate disaster scenarios with different probabilities of occurrence that closely match a real flood problem. Hence, all of data in each probabilistic scenario will able to estimate by using historical data and research data. The objective functions and constraints are formulated in a stochastic linear mixed-integer programming model that represent as follows:

Indices and index sets

I	Set of affected communities; $i \in I$
J	Set of candidate shelters; $j,\ k, \in J$
ξ	Set of possible periods; $s \in \xi$

Parameters

MS	Maximum limit of selected shelters
MB	Maximum planning budget of local government (THB)
M	A Large positive number
P_s	Probability of occurrence of a disaster in period $s \in \xi$
D_i	Population in affected community $i \in I$
PD_{si}	Proportion of population in affected community $i \in I$ need to evacuate in period $s \in \xi$
η_j	Capacity of shelter $j \in J$
C_j	Construction cost of candidate shelter $j \in J$ (THB)
R_j	Risk index of candidate shelter $j \in J$
∂_{sj}	Equal to 1 if candidate shelter $j \in J$ locate in impact level $s \in \xi$, 0 otherwise
D_{ij}^{ϑ}	Distance from affected community $i \in I$ to candidate shelter $j \in J$ (Km)
D_{jk}^{τ}	Distance from candidate shelter $j \in J$ to candidate shelter $k \in J$ (Km)

Decision variables

X_j	1 if shelter $j \in J$ is selected, 0 otherwise

TP_{sj}	Total population of shelter $j \in J$ in evacuation period $s \in \xi$
Y^{ϑ}_{sij}	1 if affected community $i \in I$ is assigned to candidate shelter $j \in J$ during evacuation period $s \in \xi$, 0 otherwise
Y^{τ}_{sjk}	1 if shelter $j \in J$ is assigned to candidate shelter $k \in J$ during evacuation period $s \in \xi$, 0 otherwise
Z^{ϑ}_{sij}	Number of people evacuates from affected community $i \in I$ to shelter $j \in J$ during evacuation period $s \in \xi$
Z^{τ}_{sjk}	Number of people evacuates from affected shelter $j \in J$ to candidate shelter $k \in J$ during evacuation period $s \in \xi$

Minimize Z1 $$E_{\xi}\left[Q\left(X_j, s\right)\right] \tag{5.1}$$

Minimize Z2 $$\sum_{j \in J} X_j * R_j \tag{5.2}$$

Subject to $$E_{\xi}[Q(X_j, s)] = \sum_{s \in \xi} P_s * Q(X_j, s) \tag{5.3}$$

$$Q(X_j, s) = \left\{\left[\sum_{i \in I}\sum_{j \in J} D^{\vartheta}_{ij} * Y^{\vartheta}_{sij}\right] + \left[\sum_{j \in J}\sum_{k \in J} D^{\tau}_{jk} * Y^{\tau}_{sjk}\right]\right\} \quad \forall s \in \xi \tag{5.4}$$

$$\sum_{j \in J} X_j \le MS \tag{5.5}$$

$$\sum_{j \in J} X_j * C_j \le MB \tag{5.6}$$

$$\sum_{s \in \xi} TP_{sj} \ge X_j \quad \forall j \in J \tag{5.7}$$

$$\sum_{s \in \xi} TP_{sj} \le X_j * \eta_j \quad \forall j \in J \tag{5.8}$$

$$\sum_{i \in I} Z^{\vartheta}_{sij} * \left(1 - \partial_{sj}\right) + \sum_{k \in J} Z^{\tau}_{skj} * \left(1 - \partial_{sj}\right) = TP_{sj} \quad \forall j \in J, s \in \xi \tag{5.9}$$

$$\sum_{j \in J} Z^{\vartheta}_{sij} * \left(1 - \partial_{sj}\right) = PD_{si} * D_i \quad \forall i \in I, s \in \xi \tag{5.10}$$

$$TP_{1,j} * \partial_{2,j} = \sum_{k \in J} Z^{\tau}_{2,jk} * \left(1 - \partial_{2,k}\right) \quad \forall j \in J \tag{5.11}$$

$$\left(TP_{2,k} * \partial_{3,k}\right) + \left(TP_{1,k} * \left(\partial_{3,k} - \partial_{2,k}\right)\right) = \sum_{k \in J} Z^{\tau}_{3,jk} * \left(1 - \partial_{3,k}\right) \quad \forall j \in J \tag{5.12}$$

$$Z^{\vartheta}_{sij} \le M * Y^{\vartheta}_{sij} \quad \forall i \in I, j \in J, s \in \xi \tag{5.13}$$

$$Z^{\tau}_{sjk} \le M * Y^{\tau}_{sjk} \quad \forall j \in J, k \in J, s \in \xi \tag{5.14}$$

$$\sum_{j \in J} Y_{sjk}^{\vartheta} \leq 1 \qquad \forall i \in I, s \in \xi \qquad (5.15)$$

$$\sum_{k \in J} Y_{sjk}^{\tau} \leq 1 \qquad \forall j \in J, s \in \xi \qquad (5.16)$$

$$X_j, Y_{sij}^{\vartheta}, Y_{sjk}^{\tau} \in \{0,1\} \qquad \forall i \in I, j \in J, s \in \xi \qquad (5.17)$$

$$ZIJ_{sij}, ZJK_{sjk} \geq 0 \qquad \forall j \in J, k \in J, s \in \xi \qquad (5.18)$$

The objective function of the model is to minimize the expected total travel distance and the expected total risk index of shelter as shown in Equation (5.1) and Equation (5.2). The expected total travel distance is expressed in Equation (5.3), where, this consists of the distance between affected community to shelter and the distance between shelter to shelter as shown in Equation (5.4). Equation (5.5) states that the total number of selected shelters cannot exceed the maximum limit of selected shelters. Equation (5.6) ensures the total planning budget cannot exceed the budget limit. Equation (5.7) guarantees that the population can be served to shelter when it is selected. Equation (5.8) states that the population served should not exceed the maximum capacity of shelters. Equation (5.9) states that the total number of population in each evacuation period. Equation (5.10) ensures that the affected people evacuate to shelter in each evacuation period should be equal to the number of expected evacuation requirements with respect to the evacuee's behavior. Note that the number of expected evacuation requirements in each scenario or period is estimated from historical data and research data. Equation (5.11) - (5.12) states the balance constraint that the number of population departure should be equal to the number of the population come. Note that ∂_{sj} present assignment protection for shelters, when the shelter is located in safety zone, the population does not need to evacuate to a new shelter. Equation (5.13) - (5.14) state that the binary variable of the assignment is set to 1 when the people in each community or each shelter is assigned to each shelter. Equation (5.15) - (5.16) ensure that affected community can be served by one shelter in each period. Equation (5.17) and (5.18) describe non-negativity and binary conditions of the decision variable.

The solution of proposed mathematical model, including the number of shelters in different evacuation periods, assignment of affected communities, total planning budget, the expected total travel distance and the expected total risk index of shelter can be calculated for the planning area, in which all of the solutions are analyzed related to the probability of occurrence. Our results can serve emergency management purposes. The first is to help in preparation stage including spatial distribution of shelter, assignment of affected communities, and expectation of planning budget under probability of occurrences. The second is to aid in response stage in order to provide evacuation flow and directions at each evacuation period. The third is to help in recovery stage for reentry process in term of distance. Note that reentry process defines as the events when the evacuees move back to their homes after disaster events [16].

5.3.3 Solution Technique

We now consider a multi-objective problem, which is more complex than single-objective optimization problem. In this chapter, we selected epsilon-constraint method for solving our problem which was produced by Haimes *et al.* [17] and an extensive discussion can be found in Chankong and Haimes [18]. The concept of this method is to maximize or minimize one objective function while the other objectives are bounded at acceptable fixed value. When we have a multi-objective function, the number of solution models is an n-1 model. Ehrgott [19] proposed the formulation of the epsilon constraint as follows:

The multi-objective formulation

Minimize or Maximize	$\left[f_1(x), f_2(x), \ldots, f_n(x)\right]$	(17)
Subject to:	$x \in X$	(18)

The epsilon-constraint formulation

Minimize or Maximize	$f_i(x)$	(19)
Subject to:	$f_j(x) \le \varepsilon_k \qquad k = 1, \ldots, p; k \ne j$	(20)
	$x \in X$	(21)
	Where $\varepsilon \in R^p$	

According to the formulation of epsilon constraint approach, we have to reformulate our proposed model in epsilon constraint form. This technique, we have to decide to set one criterion to be objective while the other objectives are bounded at acceptable fixed value. Our problem, there are two criteria, we decided to choose the first criteria to be an objective function that is to minimize the expected total travel distance (Z1) because the distance is a major criterion for evacuation planning that affects the decision of evacuee both evacuation process and reentry process [14]. While the second criteria (Z2) is set to be bound at the acceptable value in the constraint. The new formulation requires fewer constraints that shown as follows:

Addition parameters

ε_{z2} = the acceptable bound of objective Z2

Objective function

Min Z1 $\quad E_{\xi}[Q(X_j, s)]$ (22)

Constraints

$$\sum_{j \in J} X_j * R_j <= \varepsilon_{z2} \tag{23}$$

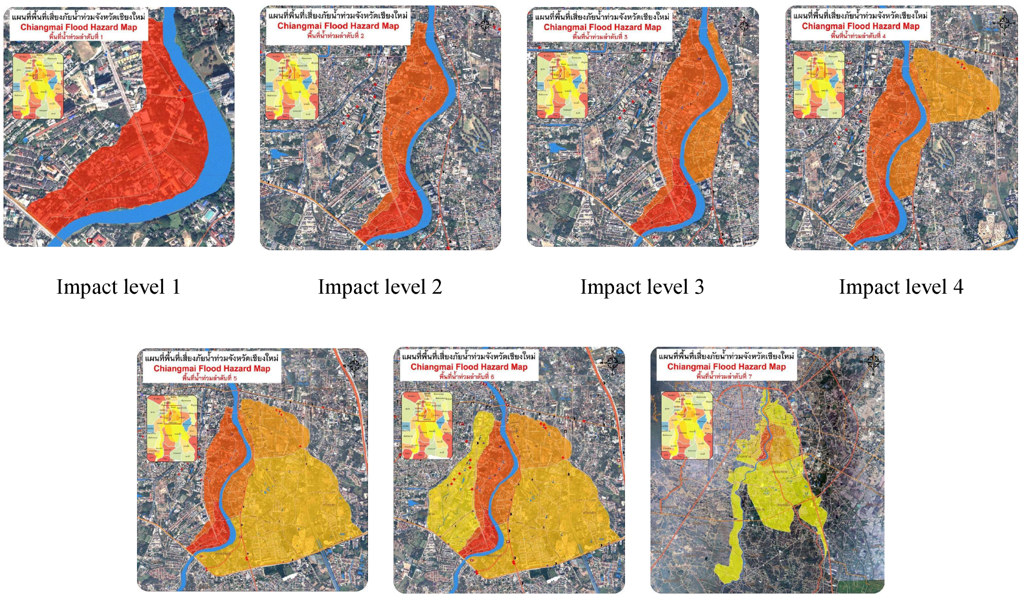
Equation (3) – (18)

5.4 Numerical Experiment

This section presents a case study; in which we apply our approach to a real case study in Chiang Mai province in Thailand. Chiang Mai is vulnerable to flooding every year due to its bowl-like shape [20]. Floods usually occur late in May – October rainy season due to masses of moist air moving from the Indian Ocean, and tropical depressions moving westward from the South China Sea [21]. Chiang Mai city was faced with large flood disasters in 2011, more than 73 communities were hit by flood disasters. Hence the government mainly emphasizes to this problem.

5.4.1 Flood hazard map of case study

Chiang Mai province implemented a flood warning system for the Ping river. This system has two gauging stations for making real-time predictions of the water level, P.67 located at Ban Mae-tae in Sansai district and P.1 in downtown Chiang Mai, in which there is distance around 32 kilometers. The water takes about seven hours for traveling to Station P.1. Therefore, the government can predict the impact on the downtown area by measuring the level of the Ping river at Station P.67. The Natural Disaster Research Unit of Civil Engineering Department of Chiang Mai University [22] has surveyed and collected floods data in Chiang Mai for a long time ago. The Chiang Mai flood hazard map is produced based on historical data from Station P.1 and P.67 since 2006 as shown in Figure 5.2, in which the risk is divided into seven levels. The number of affected communities increases with respect to the impact level, from level 1 – level 7. This disaster is unlike other natural disasters such as landslide, earthquake or tsunami. The floods typically are known about several hours before communities will be affected. For this case, the government is able to determine if people should evacuate or not in around seven hours. At present, there are two large temporary shelters for evacuation during floods situation that far from the community about 10 kilometers (No. 30 and 34). When the floods strike, the evacuee will be served by both shelters.



Impact level 1 Impact level 2 Impact level 3 Impact level 4

Impact level 5 Impact level 6 Impact level 7

Figure. 5.2 Seven impact levels of the Chiang Mai flood hazard map [22]

5.4.2 Example Data Set and Assumptions

Table 5.1 shows the probability of occurrence, the water level of Ping river and the number of affected communities in the different impact levels based on the classification of impact level by CENDRU. The data was referred from Manopiniwes and Irohara (2016). Following our conceptual model, if we determine with respect to seven impact levels, it is too much for evacuation in each level and burdensome for evacuees, especially the evacuees in the first level might have to evacuate several times. So, we assume that the seven impact levels are classified into three impact levels in which it is respected to the behavior of flooding that extends around the river, it implies that we have three evacuation periods. According to the Table 5.1, the impact level can be set as follows: the impact level 1, 2 and 3 are set in impact level 1, the impact level 4, 5 and 6 are set to impact level 2, and the impact level 7 is set to impact level 3. The geographical location of three impact levels, the probability of occurrence and affected communities are shown in Figure. 5.3 and Table 5.2. In accordance with Table 5.2, the probability of impact level 1 is the highest as 0.73 since this impact level usually faces with flood every year when compares with the other levels. In this impact level, 18 communities are hit by floods. While the probability of impact level 2 and 3 is provided as 0.25 and 0.02, respectively. The number of affected communities in impact 2 and 3 is continuously increased following the severity of flooding, in which there are 47 and 123 communities, respectively. Note that the evacuation period is defined as following the impact level.

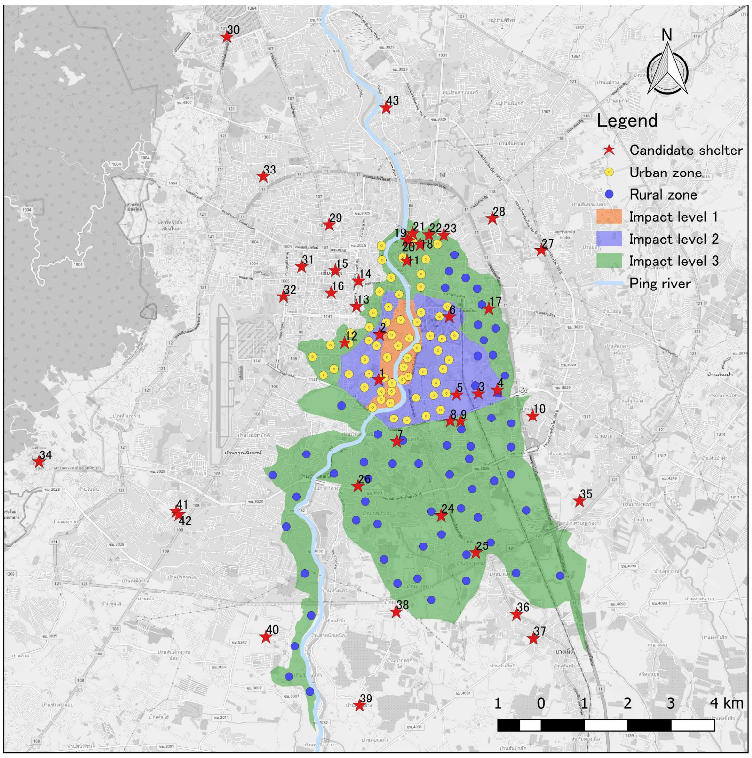


Figure. 5.3 Geographical location of three impact levels, candidate shelter, and affected communities in Chiang Mai, Thailand

Table 5.1 Classification of impact level by CENDRU

Impact level	1	2	3	4	5	6	7
Probability	0.35	0.2	0.18	0.12	0.08	0.05	0.02
Ping river at station P.1 (m)	3.7-3.9	3.9-4.0	4.0-4.1	4.1-4.2	4.2-4.3	4.3-4.6	Over 4.6
Number of affected communities	6	12	18	24	39	47	123

Table 5.2 Classification of impact level for hierarchical evacuation model

Impact level	1	2	3
Probability	0.73	0.25	0.02
Ping river at station P.1 (m)	3.7-4.1	4.1-4.6	Over 4.6
Number of affected communities	18	47	123

According to some shelters can be located in the flooding risk area, so we assume that the risk index of shelter is provided with respect to the probability of flooding or probability of impact level. For example, the shelters are located in impact level 2, the risk index of those shelters will equal to 0.25. In this study, we considered 123 affected communities in Chiang Mai city. Furthermore, we have considered the refugee population between the urban area and rural area, especially urban area (commercial land or tourism land) is a critical concern so as estimate the evacuation demand. For fulfilling demand, the estimated should determine at maximum efficiency. In an urban area, we used the number of people of the census and the expected number of tourists during May to October as shown by Equation (24). In a rural area, we used the number of people of census only for providing the demand that shown in Equation (25). The proportion of population that need to evacuate in each period is referred from Lauthep *et al.* [15], 44.81% evacuate immediately after warning signal given by local government, 8.00% evacuate when the flood level is lower than 0.5 meter, and 4.44% evacuate when the flood level is over than 0.5 meter.

$$Demand_{urban} = Pop_{cesus} + Pop_{tourists} \tag{24}$$

$$Demand_{rural} = Pop_{cesus} \tag{25}$$

Unlike other natural disasters, the temporary shelter should have large area enough for vehicle parking and refugee. Moreover, the temporary shelter should access easily and also have availability for supporting the refugee. In this respect, candidate shelter sites in this study area include schools, universities, temples and city squares. Another guideline to follow in the selection of temporary shelters should be located far from river or swamp and far from an affected area more than around 100 meters. After filtering out this area, a total 43 candidate shelters were chosen from schools, universities, and city squares that shown in Figure 5.3. More importantly, the availability of relief resources and the cost must be considered for flood shelter selection as well. The following fixed costs and variable costs are taken from the floods design directive as well as the expected planning budget of the local government. In this study, we assume that the cost of each selected shelter is calculated with respect to the capacity of its shelter, in which the cost is 200 Baht per capita. Finally, we assume that the maximum limit of budget and the maximum limit of selected shelter are 7,500,000 Baht and 25, respectively.

5.5 Computational results

We solved the model using the Gurobi Optimizer Ver. 6.0.0 mathematical programming solution software. All experiments were run on a personal computer with an Intel (R) Core (TM) i7-6700 CPU (3.40GHz) and 16 GB of RAM.

We first solve the single objective model of each objective function; consist of the expected total travel distance and the expected total risk index of shelter. We solve the problem (3) – (16) with objectives Z1 and Z2 one at a time. Table 5.3 presents the objective values of the single objective model. For the minimum expected total travel distance model, the expected total travel distance is 32.41 kilometers, while the expected total risk index of shelter is 0.64. For the minimum expected total risk index of shelter model, the expected total risk index of shelter is 0, while the expected total travel distance is 79.87 kilometers. Table 5.4 present the list of selected shelters for each single objective model. For the minimum expected total travel distance model, total selected shelter is 25 shelters. The first evacuation period, the second evacuation period, and the third evacuation period request at least 3, 9, and 15 shelters, respectively. For the minimum expected total risk index of shelter model, 5 shelters are located for the first evacuation period, while the second evacuation period and the third evacuation period request 8, and 20 shelters, respectively.

Table 5.3 Ideal values from the single objective model

Objective function value	Single objective model		Lower bound	Upper bound
	Minimize expected total travel distance	Minimize expected total risk index of shelter		
Expected total travel distance (Kilometers)	32.41	79.87	32.41	79.87
Expected total risk index of shelter	0.64	0	0	0.64

Table 5.4 Selected shelters from single objective model

Selected shelters	Single objective model	
	Minimize expected total travel distance	Minimize expected total risk index
1st Evacuation period	{1, 2, 7}	{10, 13-16}
2nd Evacuation period	{7-9, 11-13, 15, 17, 26}	{10, 13, 15, 16, 27, 28, 32, 38}
3rd Evacuation period	{10, 13, 14, 16, 27- 29, 32, 35-38, 40-42}	{10, 13-16, 27-29, 31-33, 35-43}
Total selected shelter	25 shelters	20 shelters

The results above confirm that two criteria are conflicting objectives, in which no solution simultaneously achieves all two criteria. Thus, epsilon constraint approach is applied to overcome this challenge for decision making's decision makers within relation to bi-criteria. According to the result of Table 5.3, we can construct the payoff table by simply calculating the individual optima of the objective functions. For the expected total travel distance, the upper bound and lower bound are 79.87 and 32.41 kilometers. While the upper bound and lower bound of the expected total risk index of shelter are 0.64 and 0. To design the hierarchical evacuation planning and shelter site selection under probability of occurrence for the flood disaster, we would like to present decision makers with more alternatives. Hence, we construct a bi-criteria model which considers the expected total travel distance with respect to the other criteria. According to the discussion in Section 5.3, we solve this problem using an epsilon-constraint method by formulating the problem in epsilon constraint form, the first objective function (Z1) is set to be an objective function that consists of constraint (3) – (16) and obtain an upper bound on objective Z2. The second objective is varied from upper bound to lower bound by decreasing the value in decrements of its value.

We generated the solution by minimizing the first objective (Z1) while decreasing the value of Z2 from 0.64 to 0, in decrements of 0.01, the solution was solved in 65 sub-problems as shown in Figure 5.4. From the solution, we found that the minimum expected total travel distance is ranged between 77.87 and 32.41 kilometers. Note that black circles representing non-dominated solutions and white circles represent weakly non-dominated solutions. From all solutions, we see that the best first objective value Z1 is reached at the maximum second objective value. If we decrease the second objective value with its decrements, the objective function (Z1) increase exponentially. Especially, when the value of Z2 is set between 0.32 to 0, the objective function is rapidly increased. This model contains the single objective solution of the minimum expected total travel distance model as part of the dominated set with 32.41 kilometers.

The values of the objective functions and the corresponding non-dominated solution sets of the model are presented in Table 5.5, Table 5.6 and Figure 5.5, in which there are 17 solutions. From Figure 5.4 and 5.5, we see that when the second objective is decreased, not only the minimum expected risk index of shelter but also the total number of selected shelters and planning budget are decreased. On the other hand, the first objective increases continually. The trend of this solution shown that the minimum expected total travel distance starts at upper bound with an expected total risk index of shelter estimated to be 0.64 while the planning budget is 7.1 million Baht. The objective is slightly increased when bound of the expected total risk index of shelter is set between at 0.64 and 0.56. After that, the non-dominated point jumps to 0.39 when the bound is set to be 0.55 because the shelter where locate in impact level 2 is removed from a subset of selected shelters. The non-dominated point has a big change as two-time before the trend is rapidly increased when the bound is located at 0.33 to 0. According to the bound of expected total risk index of shelter is decreased with its decrements, the shelter where locates in flooding risk area will be removed and instated with the new shelter where has less flooding risk, in which shelter selection depends on its significance.

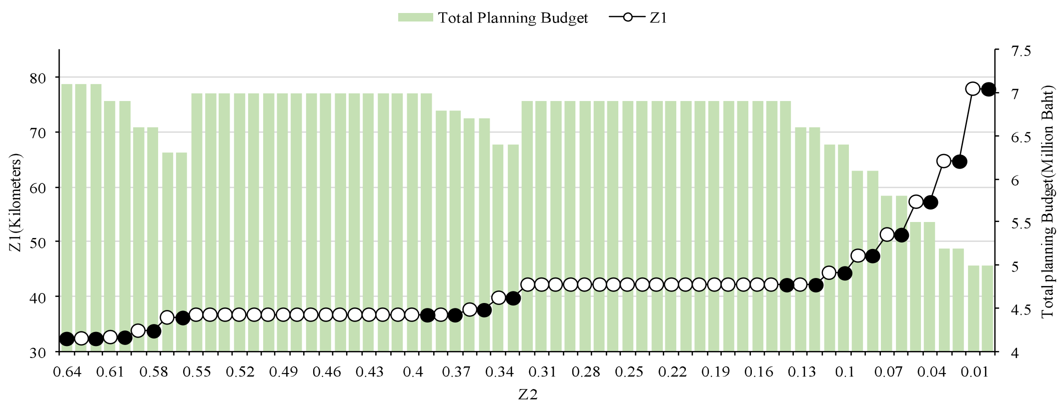


Figure 5.4 The solution point of a case study with black circles representing non-dominated solutions and white circles represent weakly non-dominated

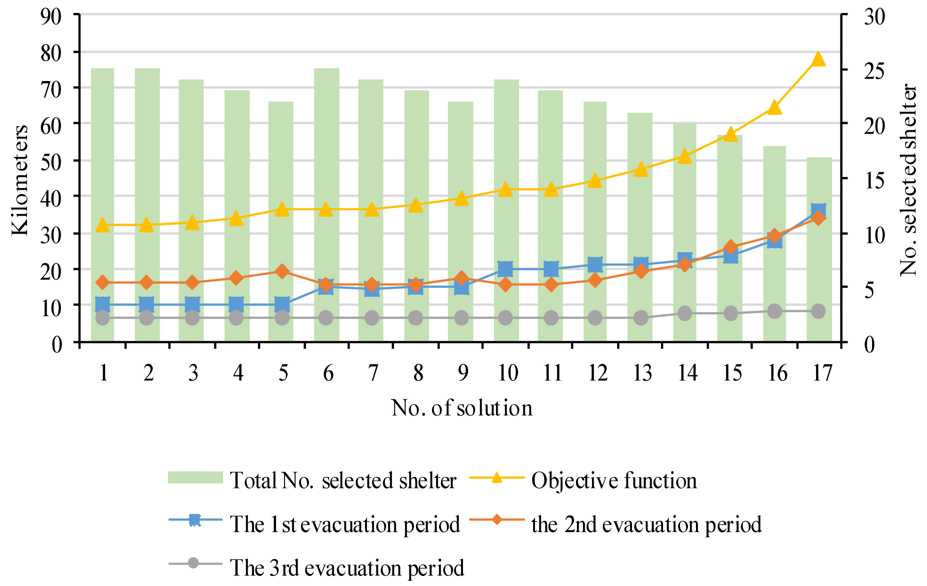


Figure 5.5 The objective solutions and non-dominated solutions

Table 5.5 The values of the objective functions and the corresponding non-dominated solution sets

No	Z1 (Km.)	Z2	The total No. of selected shelter	Planning budget (million)	Total expected travel distance (Km.)		
					The 1st period	The 2nd period	The 3rd period
1	32.41	0.64	25	7.1	9.98	16.14	6.30
2	32.42	0.62	25	7.1	9.98	16.11	6.33
3	32.53	0.60	24	6.9	9.98	16.29	6.27
4	33.76	0.58	23	6.6	9.98	17.23	6.55
5	36.14	0.56	22	6.3	9.98	19.43	6.74
6	36.72	0.39	25	7.0	14.87	15.60	6.25
7	36.72	0.37	24	6.8	14.69	15.75	6.28
8	37.51	0.35	23	6.7	15.30	15.90	6.32
9	39.72	0.33	22	6.4	15.30	17.79	6.63
10	42.18	0.14	24	6.9	20.20	15.64	6.34
11	42.22	0.12	23	6.6	20.20	15.64	6.39
12	44.30	0.10	22	6.4	21.12	16.63	6.55
13	47.51	0.08	21	6.1	21.48	19.19	6.84
14	51.24	0.06	20	5.8	22.43	21.34	7.47
15	57.19	0.04	19	5.5	23.65	25.79	7.74
16	64.58	0.02	18	5.2	27.60	28.86	8.12
17	77.87	0.00	17	5.0	35.69	33.82	8.36

Table 5.6 The selected shelter in each evacuation period of non-dominated solutions

No	The 1st evacuation period	The 2nd evacuation period	The 3rd evacuation period
1	{1, 2, 7}	{7-9, 11-13, 15, 17, 26}	{10, 13, 14, 16, 27- 29, 32, 35-38, 40-42}
2	{1, 2, 7}	{7-9, 11-13, 15, 17}	{10, 13, 14, 16, 27- 29, 31, 32, 35-38, 40-42}
3	{1, 2, 7}	{7-9, 12-15, 17}	{10, 13, 14, 16, 27- 29, 31, 32, 35-38, 40-42}
4	{1, 2, 7}	{7, 8, 10, 12-15, 17}	{10, 13, 14, 16, 27- 29, 31, 32, 35-38, 40-42}
5	{1, 2, 7}	{7, 8, 10, 13-17, 32}	{10, 13-16, 27- 29, 31, 35-38, 40-42}
6	{1, 7, 8, 11-13}	{7-9, 11-13, 17, 26}	{10, 13-16, 27- 29, 31, 32, 35-38, 40-42}
7	{1, 7, 11-13}	{7-9, 11-14, 17}	{10, 13-16, 27- 29, 31, 32, 35-38, 40-42}
8	{2, 7, 8, 12, 13}	{7-10, 12, 13, 15, 17}	{10, 13, 14, 16, 27- 29, 31, 32, 35-38, 40-42}
9	{2, 7, 8, 12, 13}	{7, 8, 10, 12-15, 17}	{10, 13, 14, 16, 27- 29, 31, 32, 35-38, 40-42}
10	{7, 8, 11-13}	{7-13, 17, 18}	{10, 13-16, 27- 29, 31, 32, 35-38, 40-42}
11	{7, 8, 11-13}	{7-13, 17}	{10, 13-16, 27- 29, 31, 32, 35-38, 40-42}
12	{7, 8, 12, 13, 17}	{7-10, 12-14, 17}	{10, 13-16, 27- 29, 31, 32, 35-38, 40-42}
13	{7, 8, 12, 13, 16}	{7-10, 12-14, 16, 28}	{10, 13, 15, 16, 27- 29, 31, 32, 35-38, 40-42}
14	{7, 8, 12-14, 16}	{7, 8, 10, 12-14, 16, 28}	{10, 13, 15, 16, 27- 29, 31, 32, 35-38, 40-42}
15	{7, 8, 13, 16}	{7, 8, 10, 13-16, 28}	{10, 13, 15, 16, 27- 29, 31, 32, 35-38, 40-42}
16	{7, 13, 14, 16}	{7, 10, 13-15, 27, 28, 38}	{10, 13-15, 27- 29, 31, 32, 35-38, 40-42}
17	{13-16}	{10, 13-16, 27, 28, 32, 38}	{13, 27- 29, 31, 32, 35-38, 40-42}

According to the probability value of the first evacuation period is the highest that showed in Table 5.2, so the first evacuation period is quite important for objective function (Z1). To find the minimum value of the objective function, the first evacuation period is firstly focused on trying to make the shortest distance and then the second and the third evacuation period are respectively considered. According to the first stage of evacuation is firstly determined, it could affect to shelter site selection and evacuation planning in the next step as well. The first evacuation period needs at least three shelters for serving the affected community that consist of shelter 1, 2 and 7. The shelters are changed when the bound of risk index of shelter is decreased, while the total distance of this period deteriorates step by step. For the second evacuation period, the main shelters start with shelter 7, 8, 9, 11, 12, 13, 15, 17, and 26. From the Table 5.6, the selected shelters from the first solution will be changed when the bound is decreased, except for the shelter 13. The shelter 13 is selected in every solution because it locates nearly by the affected zones and locates in safety area. The expected total distance in second evacuation period has fluctuation because it got an effect from removing the main shelters in the first period. However, the final range solution, the expected total travel distance is increased. For third evacuation period, all shelters are located in safety area. The expected total travel distance in this period change slightly that estimated to be 6 kilometers when the bound at 0.64-0.08. Then, the expected total travel distance is slowly increased by 9.21% (Solution No. 14) to 22.22% (Solution No. 17), based on 6.84 (Solution No. 13).

In order to provide a guideline for decision makers on selecting an efficient solution, we represent the solution point in term of the trade-off between the value of expected total travel distance and value of expected risk index of shelter in Figure 5.6. According to the single objective of the expected total travel distance, the minimum value is 32.41 kilometers, is considered to be a baseline. For decision making, the decision makers are able to see the percentage of changing in objective in each solution. Furthermore, we represent three schemes of hierarchical evacuation planning and flood shelter site location that shown in Figure 5.7.

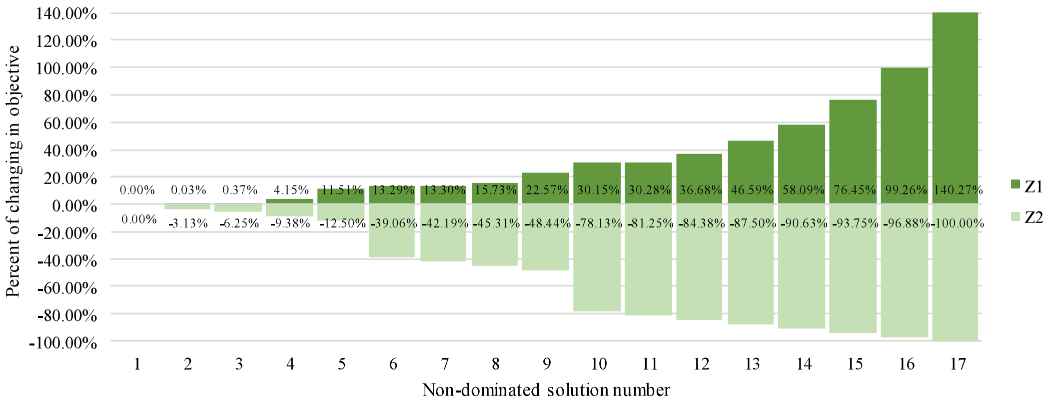
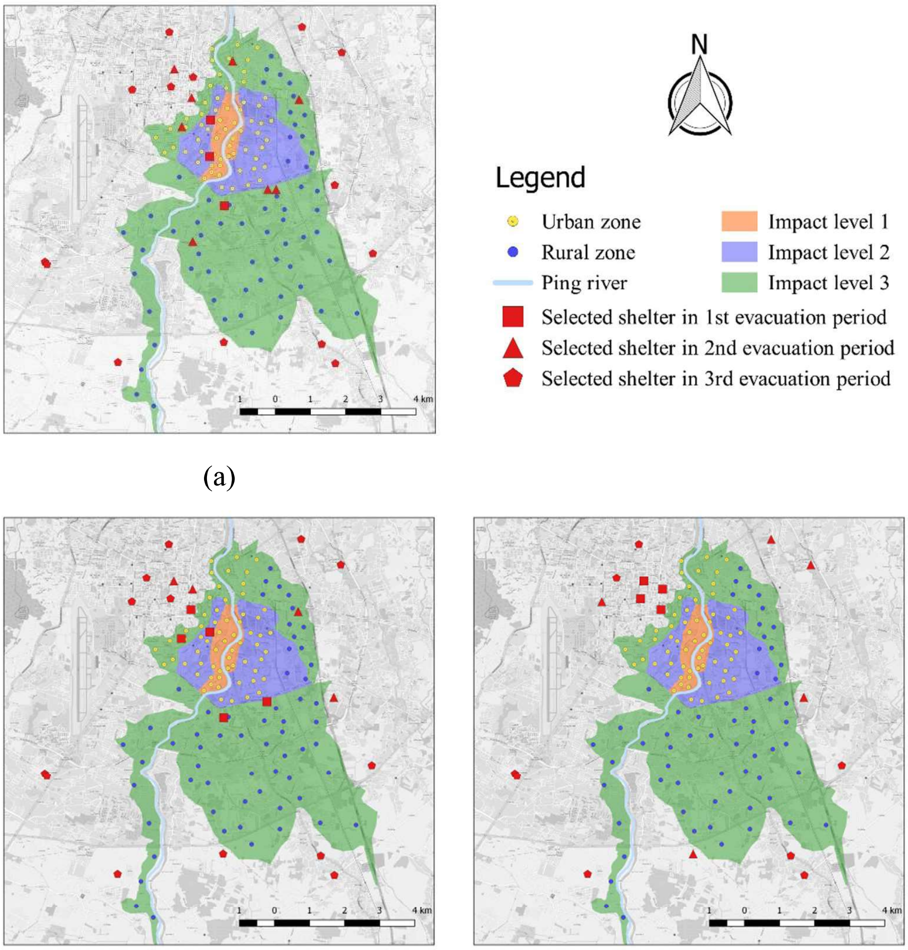


Figure 5.6 The trade-off of the expected total travel distance and the expected total risk index of shelter based on lower bound of Z1 and upper bound of Z2

To recommend for decision making's decision makers, if they focus more on the term of travel distance, they should choose the non-dominated solution no. 1, in which the expected total travel distance is 32.41 kilometers while the expected total risk index of shelter is 0.64. On the other hand, if the decision makers focus more on the term of risk index of shelter, they should choose the non-dominated solution no. 17, in which the expected total risk index of shelter is 0 while the expected total travel distance is 77.87 kilometers. From the Figure 5.6, we see that a 100% reduction in the expected total risk index of shelter is offset by a 140.27% increase in the expected total travel distance.

To enhance flood evacuation planning and flood shelter site selection, decision makers should be interested in the Pareto set because it represents the solution of a problem that there are several choices. The decision makers should carefully determine for selecting an appropriate solution. For the second objective, to fulfill the requirement of evacuees at all situations, risk index of shelter criterion must be carefully considered because this criterion is a major threat to evacuation efficiency, it may make likely that evacuee will be forced to endure a longer transfer distance [13]. Finally, the final point depends on decision maker's preference.

As stated earlier, this case study is faced with flood disaster almost every year. However, in the reality of this problem, many times there are errors and inefficient performance issues including unsuitable opened shelter site, inadequate capacity of shelter, long distance evacuation in perspective of evacuee and amiss assignment. In this study, we determined that our proposed conceptual model could overcome those happenable problems. Moreover, this could consider hierarchical evacuation concept, the evacuee's behavior, financial constraint, and the uncertain of flood events simultaneously. To compare the performance with previous evacuation plan of the case study, in which the local government always select shelter No. 30 and No. 34 for supporting evacuees whenever flooding, our model can reduce the expected travel distance to estimate be 71.41% (Scheme 17) with respect to the formulated system and can cover all of the demand points in each affected zone. Note that the binary of the other shelters is set as 0 except shelter No. 30 and 34 in the system. Although this can reduce the travel distance of evacuation, this is faced with risk problem of open shelter at potential flooding area, the assignment of this rather complicates due to the behavior of evacuees and some communities might have to evacuate several times. However, this proposed system can apply with the real-world case and respond to evacuee’s behavior and uncertain situation of flooding as well. Furthermore, although this evacuation planning is designed based on hierarchical evacuation concept, it is not necessary to evacuate following the step of plan. If the local government can predict that the severity of flooding will occur with the expensive flood, the local government can skip over the first or the second evacuation period to the next evacuation period in which this depends on the decision making’s local government.



(a)

(b)

(c)

Figure. 5.7 Three schemes of evacuation planning and flood shelter site location (a) Scheme 1 with the minimum expected total travel distance; (b) Scheme 9 with the median expected total travel distance and expected total risk index of shelter; (c) Scheme 17 with the minimum expected total risk index of shelter

To improve preparedness, the government should provide more efficient forecast. Moreover, this proposed model should consider in road closures or traffic congestion, difference of travel speed depending on the mode selection, accessibility of shelter site, and utilization of selected shelter. Besides, this should consider how to classify evacuation period in which it could affect to effectiveness of evacuation as well. The advantage of this study, when the flood disaster occurs with low-impact events, the evacuees do not need to evacuate to the shelter with a longer transfer distance. Also, the local government can reduce the budget as well.

5.6 Conclusions

This chapter proposes a stochastic linear mixed-integer programming mathematical model for developing flood evacuation planning and shelter site selection under hierarchical evacuation planning and probabilistic scenario. The proposed mathematical model considers two criteria as objective function: minimum expected total travel distance and minimum expected total risk index of shelter. The proposed model not only provides a flood shelter and population assignment but also scrutinizes hierarchical evacuation concept, evacuee's behavior and uncertainty of events. Our proposed model was validated with probabilistic scenarios due to the uncertainty that surrounds disasters and their consequence. A flood hazard map of Chiang Mai province in Thailand was used to generate disaster scenarios with different probabilities of events that closely match a real flood problem. To provide a guideline for decision makers, we proposed epsilon constraint approach to solve the proposed mathematical model in which it can handle multiple and conflicting criteria problem. This chapter presented several solutions for decision makers on selecting an efficient solution that showed expected total travel distance, expected total risk index of shelter, selected shelters, and planning budget. Furthermore, this chapter presented the solution point in term of the trade-off between the value of expected total travel distance and value of expected total risk index of shelter. This proposed model will be great significance in helping decision makers consider spatial, financial, and risk aspects of the strategic placement of flood shelters and flood evacuation planning under uncertainty of flood scenarios that balance two criteria; travel distance and risk index of shelter. In future research, the model should consider in road closures or traffic congestion, utilization of shelter and the weight associated with each demand point that may affect to an efficient evacuation. Moreover, this model should concentrate on construction cost as objective function simultaneously because it will be an advantage for the local government. However, our mathematical model can apply to any other city in flood situation as well.

5.7 References

[1] Guha-Sapir, D., Hoyois, P., Below, R. (2015). Annual Disaster Statistical Review 2014: The Numbers and Trends. Brussels: CRED.

[2] Boonmee, C., Mikiharu, A., & Takumi, A. (2017). Facility Location Optimization Model for Emergency Humanitarian Logistics. International Journal of Disaster Risk Reduction, 24, 485-498.

[3] Lim, Jr, H., Lim, M. B., & Piantanakulchai, M. (2013). A review of recent studies on flood evacuation planning. Journal of the Eastern Asia Society for Transportation Studies, 10, 147-162.

[4] Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. Operations Research, 19(6), 1363-1373.

[5] Santos, M. G., Meriño, M., Sore, N., & Quevedo V. C. (2013). Flood Facility Location-Allocation in Marikina City Using MCLP with Lagrange. Paper presented at the 14th Asia Pacific Industrial Engineering and Management Systems Conference (APIEMS), Cebu, Philippines, December 2-3.

[6] Wang, K., Chen, N., Tong, D., Wang, K., Wang, W., & Gong, J. (2016). Optimizing precipitation station location: a case study of the Jinsha River Basin. International Journal of Geographical Information Science, 30(6), 1207-1227.

[7] Chanta, S., & Sangsawang, O. (2012). Shetler-site selection during flood disaster. Paper presented at the 4th International Conference on Applied Operational Research, Bangkok, Thailand, July 25-27.

[8] Boonmee, C., Naotaka, I., Takumi, A., & Mikiharu, A. (2016). Multi-model optimization for shelter-site selection: A case study in Banta municipality, Thailand, Paper presented at the 53th infrastructure planning in Japan Society of Civil Engineers, Hokkaido, Japan, May 28-29.

[9] Kongsomsaksakul, S., Yang, C., & Chen, A. (2005). Shelter location-allocation model for flood evacuation planning. Journal of the Eastern Asia Society for Transportation Studies, 6, 4237-4252.

[10] Feng, C. M., & Wen, C. C. (2005). A bi-level programming model for allocating private and emergency vehicle flows in seismic disaster areas. Paper presented at the 11th Eastern Asia Society for Transportation Studies Conference, Cebu, Philippines, September 11-14.

[11] Mirzapour, S. A., Wong, K. Y., & Govindan, K. (2013). A capacitated location-allocation model for flood disaster service operations with border crossing passages and probabilistic demand locations. Mathematical Problems in Engineering, 2013.

[12] Salman, F. S., & Yücel, E. (2015). Emergency facility location under random network damage: Insights from the Istanbul case. Computers & Operations Research, 62, 266-281.

[13] Chen, Z., Chen, X., Li, Q., & Chen, J. (2013). The temporal hierarchy of shelters: a hierarchical location model for earthquake-shelter planning. International Journal of Geographical Information Science, 27(8), 1612-1630.

[14] Hu, Z. H., Sheu, J. B., & Xiao, L. (2014). Post-disaster evacuation and temporary resettlement considering panic and panic spread. Transportation research part B: methodological, 69, 112-132.

[15] Lauthep, P., Suwansunthon, A., Sutthiphan, S., & Taneerananon, P. (2013). Flood Evacuation Behavior Analysis in Urban Areas. Journal of the Eastern Asia Society for Transportation Studies, 10, 178-195.

[16] Hu, F., Yang, S., & Xu, W. (2014). A non-dominated sorting genetic algorithm for the location and districting planning of earthquake shelters. International Journal of Geographical Information Science, 28(7), 1482-1501.

[17] Haimes, Y. Y., Ladson, L. S., & Wismer, D. A. (1971). Bicriterion formulation of problems of integrated system identification and system optimization. IEEE Transactions on Systems Man and Cybernetics, (1), 296-297.

[18] Chankong, V., & Haimes Y. (1983). Multiobjective Decision making: Theory and Methodology, New York: Elsevier, 1983.

[19] Ehrgott M. (2005). Multicriteria Optimization. Berlin: Springer-Verlag Berlin Heidelberg.

[20] Manopiniwes, W., & Irohara, T. (2016). Stochastic optimization model for integrated decisions on relief supply chains: preparedness for disaster response. International

Journal of Production Research, 1-18.
[21] Wood, S. H., & Ziegler, A. D. (2008). Floodplain sediment from a 100-year-recurrence flood in 2005 of the Ping River in northern Thailand. Hydrology and Earth System Sciences, 12(4), 959-973.
[22] Civil Engineering Chiang Mai University Natural Disasters Research Unit (CENDRU). (2015) Chiang Mai City Flood Preparedness System. http://cendru.eng.cmu.ac.th (in Thai)

Chapter 6

Location and Allocation Optimization for Integrated Decisions on Post-Disaster Waste Supply Chain Management: On-site and Off-site Separation for Recyclable Materials

6.1 Introduction

Disaster is any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, or the deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area [1]. Since the 1950s, the magnitude and number of disasters have exponentially increased, with the number of affected people having increased in proportion (about 235 million people per annum on average since the 1990s) [2]. In 2015, 376 naturally triggered disasters were recorded, with the economic damages estimated to be US$ 70.3 billion, resulting in the deaths of 22,765 people and seriously impacting 110.3 million victims [3]. Due to an increasing number of disasters, many researchers have paid a great deal of attention to the concept of "Disaster Management (DM)" with the objective of helping at-risk persons to avoid and recover from the effects of a disaster [4]. The activity of DM consists of four major stages: mitigation, preparation, response, and recovery. One of the most important stages is the recovery stage. This stage was defined as the act of restoring the affected community or area back to a normal situation after a disaster [5]. Two of the initial and most significant perspectives of disaster recovery management involve the removal and disposal of debris from the affected communities or areas [6]. This activity is a significant one, but often an overlooked aspect that is associated with post-disaster debris management [7].

Post-disaster debris management is a discipline associated with the control of the concepts of the generation of debris, storage collection, transport and transfer, processing, recycling, reuse, and disposal. The post-disaster debris management is considered a lengthy, economic, public health engineering, conservation of nature, aesthetics, and environmental challenge with a need to consider the attitude of the public. Currently, the U.S. Federal Emergency Management Agency (FEMA) has focused exclusively on reimbursing the costs of post-disaster debris operations along with the transportation costs, disposal costs, and collection costs. Therefore, FEMA has changed its policies and announced a program offering financial incentives for municipalities in order to encourage the reuse and recycling of disaster debris [6, 8]. This is considered an opportunity to reduce the costs associated with post-disaster supply chain management. According to the policies and timeline employed by FEMA, before the disaster occurs, each community is required to provide potential debris management facilities such as debris collection sites, processing sites, recycling plants, disposal sites and market sites [9]. Generally, the recovery stage involves debris collection, where the debris is transferred from the road and curb sides to temporary processing facilities, where it may go through containment processes such as separation, sorting, grinding incineration, concrete crushing and wood chipping. After that, all or parts of the debris may be transferred to the landfill for disposal, whereas parts of it may be processed further to be recycled and either reused or sold. However, many countries have also established different strategies that are more appropriate for their own circumstances. Post-disaster debris management is a consideration of humanitarian logistics; for which comprehensive reviews have been proposed by Altay and Green [10], Galindo and Batt [11], Caunhye et al. [12], Habib et al. [13] and Boonmee et al. [2]. The literature review on post-disaster debris management primarily focuses on the qualitative analysis and the documentation of past experiences [7]. Moe [14] proposed an analysis on policies, political process priorities, problems and aspects of the waste removal process after Katrina, while Bradon et al. [15] proposed an analysis of a case history of the waste recycling efforts of the US Army Corps of Engineers in Mississippi. Additionally, Karunasena et al. [16] proposed an analysis of post-disaster debris management in developing countries based on a case study in Sri Lanka, and Brown and Milke [17] studied recycling disaster waste management based on the past experiences of five international disaster events in developed countries. Moreover, this study also proposed an analysis of the benefits in a comparison of on-site and off-site separation. Ultimately, Brown and Milke [17] recommended that it is possible to have an integrated model where selected materials are separated on-site while the rest would go to an off-site separation facility. Not only have these academic papers described potential management techniques, but some organizations have also proposed guidelines for the post-disaster debris operations such as FEMA [18], USPEA [19], UNEP [20] and EPA [21]. Notably, an intensive summary article has been published and presented by Brown et al. [2], Reinhart and McCreanor [23], McEntire [24], and Ekici et al. [25].

According to the facility location problems (FLP) that exist and the fact that the flow debris decision-making process has been based on post-disaster debris supply chain management, an optimization technique has been proposed that can potentially overcome this challenge. The optimization technique has been applied to address the relevant humanitarian logistics problems and to attempt to achieve positive results. Table 6.1 presents the important characteristics of the existing studies in this area comprising the objective function, mathematical model, exact approach, algorithm solution, structure of network, and type of separation. Fetter and Rakes [6] proposed a mixed-integer linear programming model for decision-making with regard to the location of the processing sites, aspects of processing availability, and the flow of disaster waste from each affected community to the relevant site and processing networks. This study aims to minimize the total costs of the debris management operations with consideration of the fixed and variable costs of debris collection, RSR costs (Reduction, Separation and Recycling Operations) and disposal costs while including the potential revenue of saleable debris. The method of separation being employed uses the off-site separation model. A case study in Chesapeake has been proposed for validating this model. Hu and Sheu [26] proposed the linear programming model in which this study focuses on the transportation, recycling, storage of disaster waste throughout the disaster recovery stage. The objective function aims to minimize the reverse logistical costs, psychological cost and risk penalty. Hu and Sheu [26] have recommended that the storage and separation techniques should be employed at the on-site stage of management. The system employed in Wenchuan City in China has been proposed in this study. Lorca et al. [7] proposed a decision-support tool for a post-disaster waste management system. The mathematical model being proposed optimizes the selection of the processing site, processing capacities, and debris flow decision-making that are related to the collection, transport and disposal systems. Moreover, this study has also considered balancing the costs and duration of the relevant disaster waste operation systems. Pramudita et al. [27] presented a location-capacitated arc routing problem that emphasizes the debris collection sites. The goal of this model is to minimize the travel costs and the costs of establishing intermediate depots in which tabu search meta-heuristics have been proposed to find an acceptable solution. Kim et al [28] proposed selecting a temporary debris management site for the effective debris operation system by using both geographical analysis and optimization analysis. The objective of this was to minimize the total hauling distance for the transportation services in which the shortest path algorithm was applied in response to this problem. Onan et al. [29] proposed the employment of a framework to determine the location of a temporary disaster management facility with the objective of cost minimization and risk minimization from hazardous waste exposure. They determined the criteria for the planning of the collection and transportation of disaster debris. Moreover, Habib and Sarkar [30] presented a two-phase framework for sustainable waste management in the response phase of disasters in which the Analytical Network Process (ANP), fuzzy TOPSIS and Optimization technique have been proposed to identify the suitable temporary disaster debris management site.

Table 6.1 Review study of the optimization model for post-disaster debris management

Author	Objective	Math model	Exact approach	Algorithm	FLP				On/Off site separation
					S	R	L	M	
Fetter and Rakes [6]	Total cost (The fixed and variable costs of debris collection, RSR, and disposal and revenue)	MILP	Excel	-		*			Off-site separation
Habib and Sarkar [30]	Total transport cost	LP	LINGO	-		None			On-site separation
Hu and Sheu [26]	Total reverse logistical costs, psychological cost, risk penalty	LP	CPLEX	-		None			On-site separation
Kim et al [28]	Total hauling distance	MILP	-	Shortest path algorithm/ GIS		*			On-site separation
Lorca et al [7]	Total cost (Financial cost, Environmental cost, revenue and total time (Collection time and disposal time)	MILP	Excel	-		*			Mixed model separation
Onan et al [29]	Total cost and risk	MILP	-	NSGA-II	*				Off-site separation
Pramudita et al [27]	Total cost (The travel cost and the cost of establishing intermediate depots)	MILP	-	Tabu search	*				None
This work	Total cost (The fixed and variable costs of debris collection, RSR, disposal, environmental penalty cost, and revenue)	MILP	LINGO	PSO and DE (Large problem)	*	*	*		Mixed model separation

Note: S= storage and separation site, R = processing and recycling site, L = landfill, M = market, LP = linear programming, MILP = mixed integer linear programming.

Following on from the previous research studies, an effective post-disaster debris management strategy still needs to be further developed for optimum efficiency. Several studies have considered addressing a number of problems associated with developing the effective post-disaster debris operations such as those by Brown and Milke [17] and Hu and Sheu [26]. The integrated decision-making process for the on-site and off-site separation of recyclable materials is an issue that has been recommended by many research papers in order to develop an effective post-disaster waste supply chain management system. According to the previous research studies, the merits of the on-site and off-site separation systems for recyclable materials in an overall post-disaster waste supply chain management system are not well known [17]. The post-disaster debris supply chain management system now being employed that uses the optimization technique is lacking in consideration of an integrated decision-making process for the on-site and off-site separation of recyclable materials and the consideration of all networks simultaneously (debris collection sites, processing sites, disposal sites and market sites). Furthermore, an algorithm employed to solve the larger problem is lacking due to certain competence limitations of the exact solution method. Therefore, we aim to propose a developed post-disaster waste supply chain management strategy by using the location and allocation optimization tools under the integrated decision-making system for the on-site and off-site separation of recyclable materials. There are two goals of this chapter. Our first goal is to develop the post-disaster debris supply chain management strategy under an integrated decision-making system for on-site and off-site separation in handling recyclable materials using the optimization technique. The network structure considers waste collection and separation sites, processing sites, disposal sites and market sites. Our proposed mathematical model aims to select the suitable sites for post-disaster waste management system, including the collection and separation sites, processing sites and landfills, in order to provide a debris flow decision-making system as a supply chain while minimizing the total costs incurred in that the supply chain. The total costs consist of fixed and variable costs associated with the debris collection process, RSR, the disposal process, environmental penalty costs and takes into account revenue incurred from any sellable waste. Our second goal is to propose solution algorithms for the larger problem and this chapter aims to propose solutions that are representative of two metaheuristics (Particle Swarm Optimization: PSO and Differential Evolution: DE) to address the problem.

The remainder of this chapter is organized as follows: Section 6.2 presents the background study of the structure of the post-disaster waste management process, particle swarm optimization and differential evolution for the purposes of finding a solution to this problem. Section 6.3 presents the conceptual model of the post-disaster waste supply chain management (PWSCM) strategy and formulates a mathematical model for the proposed system. Section 6.4 presents the solution algorithms of PSO and DE intended to address the problem. Section 6.5 proposed computational experiments for the PWSCM model. Finally, a conclusion is given in Section 6.6.

6.2 Background study

6.2.1 Structure of post-disaster waste management system

Waste management or waste disposal requires the management of waste from the upstream stage to the downstream phase of the system. The process of the waste supply chain management consists of storage, collection, transport and transfer, processing, reuse and recovery, and the disposal of solid waste according to the best principles of economics, public health, engineering, the conservation of nature, aesthetics and the environment [16]. All of the activities are very important to the efficiency of the overall operation. Typically, the debris removal operation normally occurs in two phases: initial debris clearance activities and debris removal activities [18]. The waste collection activity begins after the emergency access routes are cleared and police, firefighters and other first responders have gained necessary access. The transport and transfer activity is initiated for the transfer of waste to relevant sites such as collection sites, separation sites, processing sites, recycling sites and disposal sites. The processing activity is begun after the waste is collected. The waste can be processed in two ways by either composting or recycling it. Both of these activities should be conducted according to the market specifications of each material; therefore, a certain amount of technology and specific plant equipment are required in the operation for the purposes of grading, sorting, etc. After composting and recycling debris, the remaining material should be properly disposed of in a landfill [16]. According to the process of waste management, there are some common criteria that affect the degree to which waste management is effectively carried out such as the consideration of costs, environmental impacts, the volume of waste, the degree of mixing of that waste, human and environmental health hazards, the areal extent of the waste, community priorities and funding mechanisms [17]. Moreover, the major structural issue that decision-makers must face when planning a post-disaster waste management recycling strategy is whether or not to separate the recyclable materials and where this should be done; otherwise referred to as on-site and off-site recycling, as is shown in Figure 6.1.

The separation of recyclable materials is a key part of the main structure that can affect the feasibility of the act of recycling. The separation of recyclable materials can be segregated into two approaches; on-site and off-site separation. Normally, separation can be achieved primarily on-site, with all waste being sorted either manually (by hand) or mechanically into a separate pile for removal and to identify the materials intended for off-site recycling sites, landfills and markets. This is commonly known as "on-site separation". Another alternative is normally known as "off-site separation". This is where all waste is transported off-site to separate processing depots for separation and recycling where the waste is then removed to landfills and markets. In this activity, the managers must consider four main criteria: (1) time constraints, (2) resource availability, (3) the necessary degree of mixing of the waste and (4) the presence of any potential human and environmental hazards. In this situation, decision-makers need to determine the potential location for the debris management site planning process and the need to select the appropriate strategy for each case. The advantages and disadvantages of each approach are well known and are shown in Table 6.2.

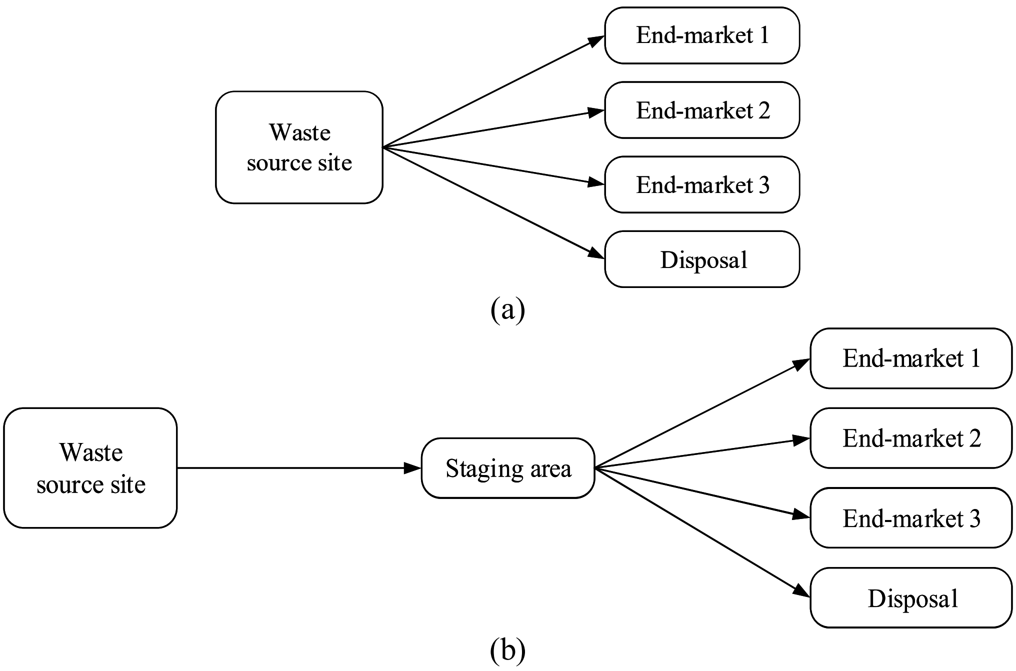


Figure 6.1 Conceptual model of on-site and off-site recycling systems [17];
(a) on-site separation; (b) off-site separation.

Table 6.2 Advantages and disadvantages of on-site and off-site separation processes (adapted from New Zealand Department of Labor [31])

	On-site separation	Off-site separation
Advantages	• Higher recycling rates • Lower recycling costs, revenues paid for some materials • Often a cleaner, safer worksite	• Only one or two containers on-site • No need for workers to separate materials for recycling • Easier logistics • One market; less information to manage
Disadvantages	• Multiple containers on site • Workers must separate materials for recycling • More complex logistics • Multiple markets; more information to manage	• Lower recycling rates • Higher recycling costs

6.2.2 Metaheuristics

As mentioned in the introduction, this chapter was motivated by the limitations of applying PSO and DE to solve post-disaster waste management problems. Hence, this chapter focused on applying two effective metaheuristics – Particle Swarm Optimization (PSO) and Differential Evolution (DE) – to plan the post-disaster waste management process in order to minimize the total cost of the supply chain. The search procedures of each algorithm are described in the following sections.

1. Particle swarm optimization

Particle swarm optimization (PSO) is a population dynamics-based optimization method that imitates the physical movements of individuals in the swarm as a searching mechanism (the concept originated from research on the group behavior of birds). The PSO has increasingly gained attention from researchers for the purposes of solving many optimization problems. The PSO algorithm was proposed by Kennedy and Eberhart in 1995 and described a proposed solution being represented by a particle, and the accumulation of the potential solutions is called "a swarm of particles" [32]. Each particle consists of elements of position and velocity. The concept of a basic PSO algorithm is to learn from the cognitive knowledge of each particle and the social knowledge of the swarm to guide particles to a better position. The swarm is randomly initialized as particles with *d* dimensions. Each particle flies to a new position with its own assigned velocity. When a new position is reached, the best position of each particle and the best position of the swarm are updated. Then, the new position is sought again with the adjusted velocity is based on its experience. The cycle is repeated until a stopping criterion is met. The process of the basic PSO algorithm, including the velocity, and position in each iteration step, is updated by equation (6.1) and equation (6.2). The evolution procedures of PSO are illustrated in Figure 6.2.

$$\omega_{id}(t+1) = w(t)\omega_{id}(t) + c_p u\left(\psi_{id}^{p} - q_{id}(t)\right) + c_g u\left(\psi_{id}^{g} - q_{id}(t)\right) \tag{6.1}$$

$$q_{id}(t+1) = q_{id}(t) + \omega_{id}(t) \tag{6.2}$$

Where,

$\omega_{id}(t)$: Velocity of i^{th} particle at the d^{th} dimension in the t^{th} iteration

$w(t)$: Inertia weight in the t^{th} iteration

$q_{id}(t)$: Position of i^{th} particle at the d^{th} dimension in the t^{th} iteration

$\psi_{id}^{p}(t)$: Personal best position of i^{th} particle at the d^{th} dimension in the t^{th} iteration

$\psi_{id}^{g}(t)$: Global best position of i^{th} particle at the d^{th} dimension in the t^{th} iteration

c_p : Weight of personal best position term

c_g : Weight of global best position term

u : Uniform random number in the interval [0,1]

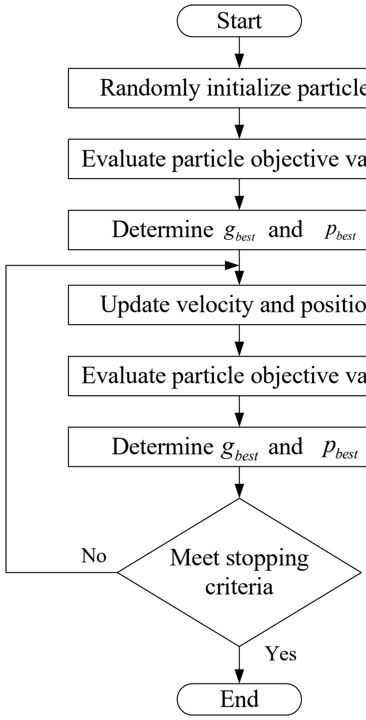


Figure 6.2 The evolution procedures of PSO [33]

2. Differential Evolution

Differential Evolution (DE) was first proposed by Storn and Price in 1995 for the purposes of global optimization over continuous search spaces [34]. DE has continually received increased levels of attention from academicians for solving many combinatorial NP-hard problems, due to its advantage of having relatively few control variables, but performing well in its search ability and convergence with less effort of computational times. DE is a population-based random search approach that is like other Evolutionary Algorithms (EAs). DE starts with a randomly generated initial population of size N. The population is represented by d dimensional vector, in which each variable value in the d dimensional space is represented by a real number. The idea of DE is its mechanism for generating a new solution using two key ideas; particular mutation and crossover operations. At the initialization stage (g = 0), the j^{th} value of the i^{th} vector is generated according to the following equation (6.3). The upper bound

(b_U) and lower bound (b_L) for the value in each dimension j^{th} (j =1, 2, 3, …, d) must be specified, where u is uniformly random in the range [0,1]. The concept of the mutation operation of DE is achieved by combining randomly selected vectors in order to produce a mutant vector. For each target vector (X_i^g) at generation g, the mutant vector (V_i^g) is generated as is shown in equation (6.4). Where X_{r1}, X_{r2}, X_{r3} are vectors randomly selected from the current population. They are mutually exclusive and different from the target vector (X_i^g). F is a scale factor that controls the scale of the differences of the vectors between X_{r2} and X_{r3}. The DE applies a crossover operator on X_i^g and V_i^g to produce the trial vector (Z_i^g). In this research, binomial crossover is applied in which the trial vector is formulated by the following equation (6.5). C_r is the crossover probability in the interval [0,1]. and j_u is a randomly chosen index ($j_u \in \{1, 2, \ldots, D\}$). The C_r value controls the probability of selecting the value in each dimension from a mutant vector over its corresponding target vector. Next, the replacement or selection of an individual occurs only if the trial vector outperforms its corresponding vector. As a result, all individuals in the next generation are as good as or better than their counterparts in the current generation. The evolution procedure of the DE population continues through repeat cycles of the three key operations; mutation, crossover and selection until certain stopping criteria are met. See more details in [35] and [36]. The evolution procedures of DE are illustrated in Figure 6.3.

$$x_{i,j}^0 = u*(b_U - b_L) + b_L \tag{6.3}$$

$$V_{i,j} = X_{r1}^g + F(X_{r2}^g - X_{r3}^g) \tag{6.4}$$

$$z_{i,j}^g = \begin{cases} v_{i,j}^g, if\ u_j \le C_r\ or\ j = j_u \\ x_{i,j}^g, \quad otherwish \end{cases} \tag{6.5}$$

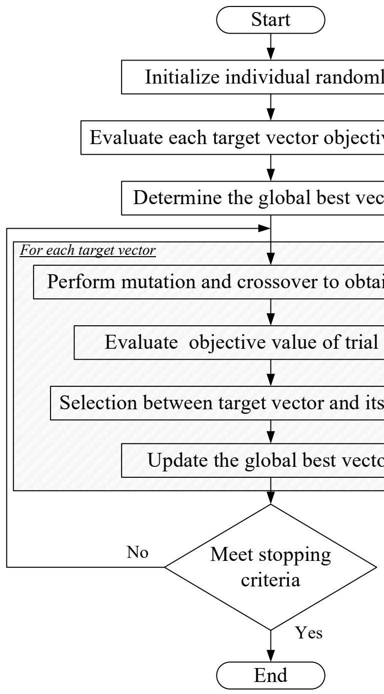


Figure 6.3 The evolution procedures of DE [36]

6.3 Post-disaster waste supply chain management (PWSCM) model

6.3.1 Conceptual model

The framework of the PWSCM model is designed with respect to a hierarchical model as is shown in Figure 6.4. This conceptual model is developed and modified from Fetter and Rakes [6] and Lorca et al. [7]. The structure of this study considers all networks in the supply chain consisting of the affected zones, temporary disaster waste collection and separating centers (TDWCSC), temporary disaster waste processing and recycling centers (TDWPRC), landfills, and markets. According to Brown and Milke [17], it has been proposed that the on-site and off-site separation should be simultaneously applied since both approaches have different advantages. When both approaches are merged, the post-disaster waste management process will be able to balance the advantages and disadvantages of both approaches. This integrated strategy was employed in the 2011 Great East Japan Earthquake and the Canterbury earthquakes (see more details of assessment in [17]). Thus, this criterion is taken to apply in the PWSCM model. In our conceptual model, the process is separated into three stages that consist of: (1) collection and on-site or off-site separation, (2) off-site processing and recycling, (3) waste disposal and waste selling. Figure 6.4 reveals that in Stage 1, debris removal is initiated after the emergency access routes are cleared. The waste is assigned from the affected zones to TDWCSCs or TDWPRCs for collection and separation by manual or preliminary technologies. In this stage, the mixed model of on-site and off-site separation is applied. The waste in some affected communities is separated on-site by a TDWCSC, while the rest is transferred to an off-site separation facility identified as TDWPRC. In Stage 2, the separated waste at the TDWCSCs is divided into three parts. The first part is transferred to TDWPRCs for processing and recycling; the second part is transferred to landfills for waste disposal; the third part is transferred to markets for selling (reuse). After the waste is processed and recycled using a variety of technologies at the TDWPRCs, the final operation will be started. In stage 3, the waste at the TDWPRCs is classified into two separate stages for the disposal of the remaining waste and the selling of the sellable or reusable waste. The remaining waste at the TDWPRCs is allocated to the landfill for disposal, while the rest is transferred to the market for selling, respectively.

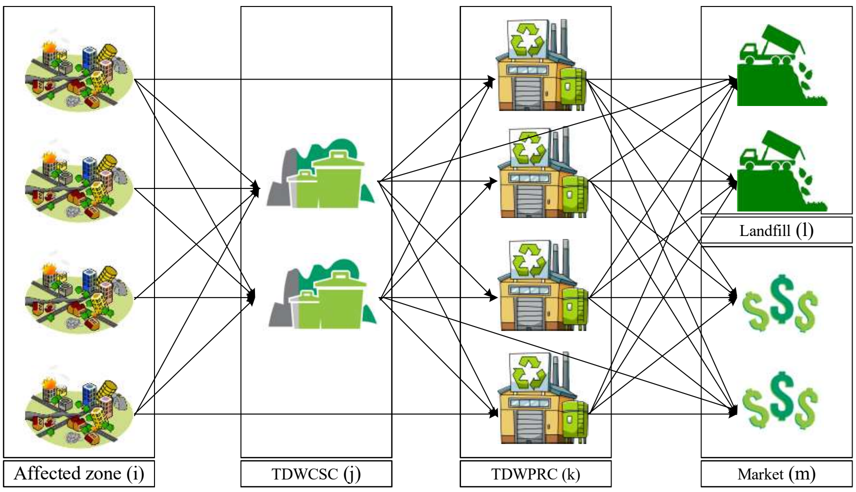


Figure 6.4 The conceptual model of post-disaster waste supply chain management strategy

6.3.2 Proposed mathematical model

According to the conceptual model, we have modified the general facility location model and distribution model to formulate a model for the PWSCM strategy. The proposed mathematical model is formulated as a mixed-integer linear programming problem (MIP), and its basic assumptions are listed as follows:

- The structure of PWSCM strategic consists of affected zones, TDWCSCs, TDWPRCs, landfills, and markets.
- To protect bafflement of assignment, this study provides the assumptions for debris flow decisions as follows; each affected zone can be served by one node from TDWCSC or TDWPRC, each TDWCSC can be served by one landfill and one market, the waste from each TDWCSC that need to be treated with each RSR technology can be served by one TDWPRC and each TDWPRC can be served by one market.
- The capacity of the market is assumed to be infinite.
- All saleable waste types can be sold at all markets.
- All waste needs to be separated before it is assigned for recycling, disposal, and sale.

Based on the above assumptions and definitions, the PWSCM model has been formulated to obtain optimal solutions that minimize the total cost in the supply chain. The output of this model aims to select TDWCSCs, TDWPRCs, and landfills, minimize financial costs, minimize the effects on humans and the environment, maximize revenue and provide debris flow decisions throughout the supply chain.

The following notions and parameters are used:

I:	Number of affected zones (i = 1, 2, …, I)
J:	Number of possible TDWCSC facility locations (j = 1, 2, …, J)
K:	Number of possible TDWPRC facility locations (k = 1, 2, …, K)
L:	Number of landfill facility locations (l = 1, 2, …, L)
M:	Number of markets (m = 1, 2, …, M)
N:	Number of RSR technologies (n = 1, 2, …, N)
H_i:	Volume of debris in affected zone i
γ_n:	Proportion of debris from affected zone that is eligible to be treated with RSR technology n
η_n:	Proportion of reduced debris from RSR technology n saleable as recycled material
ρ_n:	Proportion of reduced debris from RSR technology n for disposal
U^{TDWCSC}:	Maximum of selected TDWCSC
U^{TDWSRC}:	Maximum of selected TDWPRC
$U^{Landfill}$:	Maximum of selected landfill
P_T:	Fraction of penalty cost from transporting debris
P_O:	Fraction of penalty cost from operating debris
F_j^{TDWCSC}:	Fixed cost of opening and closing TDWCSC at location j
F_k^{TDWSRC}:	Fixed cost of opening and closing TDWPRC at location k
$F_l^{Landfill}$:	Fixed cost of opening and closing landfill at location l
V_j^{TDWCSC}:	Fixed cost of making separated technology at TDWCSC location j (On-site)
V_{kn}^{TDWSRC}:	Fixed cost of making RSR technology n at TDWPRC location k

	(Off-site)
O_j^{TDWCSC}:	Operated cost at TDWCSC location *j*
O_{kn}^{TDWSRC}:	Operated cost RSR technology *n* at TDWPRC location *k*
$O_l^{Landfill}$:	Operated cost at landfill *l*
C_j^{TDWCSC}:	Capacity of TDWCSC at location *j*
$C_l^{Landfill}$:	Capacity of landfill at location *l*
C_{kn}^{RSR}:	Capacity of RSR technology *n* at TDWPRC location *k*
δ_m:	Revenue from saleable portion of debris at market *m*
Ca_{ij}:	Cost of transporting debris from affected zone *i* to TDWCSC *j*
Cb_{ik}:	Cost of transporting debris from affected zone *i* to TDWPRC *k*
Cc_{jk}:	Cost of transporting debris from TDWCSC *j* to TDWPRC *k*
Cd_{jl}:	Cost of transporting debris from TDWCSC *j* to landfill *l*
Ce_{jm}:	Cost of transporting debris from TDWCSC *j* to market *m*
Cf_{kl}:	Cost of transporting debris from TDWPRC *k* to landfill *l*
Cg_{km}:	Cost of transporting debris from TDWPRC *k* to market *m*

The following decision variables are used:

$x_j = \begin{cases} 1, \\ 0, \end{cases}$	If TDWCSC is opened at location *j* Otherwise
$y_k = \begin{cases} 1, \\ 0, \end{cases}$	If TDWPRC is opened at location *k* Otherwise
$z_l = \begin{cases} 1, \\ 0, \end{cases}$	If landfill is opened at location *z* Otherwise
$w_{kn} = \begin{cases} 1, \\ 0, \end{cases}$	If RSR technology *n* is available at TDWPRC *k* Otherwise
a_{ij}:	Volume of debris from affected zone *i* to TDWCSC *j*
b_{ik}:	Volume of debris from affected zone *i* to TDWPRC *k*
c_{jkn}:	Volume of debris from TDWCSC *j* to TDWPRC *k* for recycling by RSR technology *n*
d_{jl}:	Volume of debris from TDWCSC *j* to landfill *l*
e_{jm}:	Volume of debris from TDWCSC *j* to market *m*
f_{kl}:	Volume of debris from TDWPRC *k* to landfill *l*
g_{km}:	Volume of debris from TDWPRC *k* to market *m*
$\xi a_{ij} = \begin{cases} 1, \\ 0, \end{cases}$	If the volume of debris from affected zone *i* is assigned to TDWCSC *j* for recycling by RSR technology *n* Otherwise
$\xi b_{ik} = \begin{cases} 1, \\ 0, \end{cases}$	If the volume of debris from affected zone *i* is assigned to TDWPRC *k* Otherwise
$\xi c_{jkn} = \begin{cases} 1, \\ 0, \end{cases}$	If the volume of debris from TDWCSC *j* is assigned to TDWPRC *k* Otherwise
$\xi d_{jl} = \begin{cases} 1, \\ 0, \end{cases}$	If the volume of debris from TDWCSC *j* is assigned to landfill *l* Otherwise
$\xi e_{jm} = \begin{cases} 1, \\ 0, \end{cases}$	If the volume of debris from TDWCSC *j* is assigned to market *m* Otherwise

$$\xi g_{km} = \begin{cases} 1, & \text{If the volume of debris from TDWPRC } k \text{ is assigned to market } m \\ 0, & \text{Otherwise} \end{cases}$$

The following auxiliary variables are used:

FC: Total fixed cost
TC: Total transport cost
OC: Total operation cost
PC: Total penalty cost for activities with environmental impact
R: Total revenue

The mathematical model of the problem is formulated as follows:

Minimization of Total Cost:

$$\text{Min } Z = FC + TC + OC + PC - R \tag{6.6}$$

Subjected to constraints;

$$FC = \sum_j F_j^{TDWCSC} x_j + \sum_k F_k^{TDWSRC} y_k + \sum_l F_l^{Landfill} z_l + \sum_j V_j^{TDWCSC} x_j + \sum_k \sum_n V_{kn}^{TDWSRC} w_{kn} \tag{6.7}$$

$$\begin{aligned} TC = & \sum_i \sum_j Ca_{ij} a_{ij} + \sum_i \sum_k Cb_{ik} b_{ik} + \sum_j \sum_k Cc_{jk} c_{jk} + \sum_j \sum_l Cd_{jl} d_{jl} + \sum_j \sum_m Ce_{jm} e_{jm} \\ & + \sum_k \sum_l Cf_{kl} f_{kl} + \sum_k \sum_m Cg_{km} g_{km} \end{aligned} \tag{6.8}$$

$$\begin{aligned} OC = & \sum_i \sum_j O_j^{TDWCSC} a_{ij} + \sum_i \sum_j \sum_k \sum_n O_{kn}^{TDWSRC} \left(b_{ik} \gamma_n + c_{jkn}\right) \\ & + \sum_j \sum_k \sum_l O_l^{Landfill} \left(d_{jl} + f_{kl}\right) \end{aligned} \tag{6.9}$$

$$PC = P_T TC + P_O OC \tag{6.10}$$

$$R = \sum_j \sum_k \sum_m \delta_m \left(e_{jm} + g_{km}\right) \tag{6.11}$$

$$\sum_j x_j \leq \mathrm{U}^{TDWCSC} \tag{6.12}$$

$$\sum_k y_k \leq \mathrm{U}^{TDWSRC} \tag{6.13}$$

$$\sum_l z_l \leq \mathrm{U}^{Landfill} \tag{6.14}$$

$$\sum_i a_{ij} \leq C_j^{TDWCSC} x_j \qquad \forall j \tag{6.15}$$

$$\sum_i b_{ik} \gamma_n + \sum_j c_{jkn} \leq C_{kn}^{RSR} w_{kn} \qquad \forall k, n \tag{6.16}$$

$$w_{kn} \leq y_k \qquad \forall k, n \tag{6.17}$$

$$\sum_j d_{jl} + \sum_k f_{kl} \leq C_l^{Landfill} \qquad \forall l \tag{6.18}$$

$$\sum_j a_{ij} + \sum_k b_{ik} = H_i \qquad \forall i \tag{6.19}$$

$$\sum_i a_{ij} \gamma_n = \sum_k c_{jkn} \qquad \forall j, n \ (n = 2, \dots, N) \tag{6.20}$$

$$\sum_i a_{ij}\,\eta_1\left(1-\sum_{n=2}^{N}\gamma_n\right)=\sum_l d_{jl} \qquad \forall j \qquad (6.21)$$

$$\sum_i a_{ij}\,\rho_1\left(1-\sum_{n=2}^{N}\gamma_n\right)=\sum_m e_{jm} \qquad \forall j \qquad (6.22)$$

$$\sum_i b_{ik}\,\eta_1\left(1-\sum_{n=2}^{N}\gamma_n\right)+\sum_i\sum_{n=2}^{N} b_{ik}\,\gamma_n\eta_n+\sum_j\sum_n c_{jkn}\,\eta_n=\sum_l f_{kl} \qquad \forall k \qquad (6.23)$$

$$\sum_i b_{ik}\,\rho_1\left(1-\sum_{n=2}^{N}\gamma_n\right)+\sum_i\sum_{n=2}^{N} b_{ik}\,\gamma_n\rho_n+\sum_j\sum_n c_{jkn}\,\rho_n=\sum_m g_{km} \qquad \forall k \qquad (6.24)$$

$$\sum_j \xi a_{ij}+\sum_k \xi b_{ik}\le 1 \qquad \forall i \qquad (6.25)$$

$$\sum_k \xi c_{jkn}\le 1 \qquad \forall j,n \qquad (6.26)$$

$$\sum_l \xi d_{jl}\le 1 \qquad \forall j \qquad (6.27)$$

$$\sum_m \xi e_{jm}\le 1 \qquad \forall j \qquad (6.28)$$

$$\sum_m \xi g_{km}\le 1 \qquad \forall k \qquad (6.29)$$

$$a_{ij}\le LN\xi a_{ij} \qquad \forall i,j \qquad (6.30)$$

$$b_{ik}\le LN\xi b_{ik} \qquad \forall i,k \qquad (6.31)$$

$$c_{jkn}\le LN\xi c_{jk} \qquad \forall j,k,n \qquad (6.32)$$

$$d_{jl}\le LN\xi d_{jl} \qquad \forall j,l \qquad (6.33)$$

$$e_{jm}\le LN\xi e_{jm} \qquad \forall j,m \qquad (6.34)$$

$$g_{km}\le LN\xi g_{km} \qquad \forall k,m \qquad (6.35)$$

$$x_j, y_k, z_l, w_{kn}, \xi a_{ij}, \xi b_{ik}, \xi c_{jk}, \xi e_{jm}, \xi f_{kl}, \xi g_{km}\in\{0,1\} \qquad \forall j,k,l,m,n \qquad (6.36)$$

$$a_{ij}, b_{ik}, c_{jkn}, d_{jl}, e_{jm}, f_{kl}, g_{km}\ge 0 \qquad \forall i,j,k,l,m,n \qquad (6.37)$$

The objective of the proposed model is to minimize the total costs associated with the management of the debris removal supply chain in post-disaster scenarios as is shown in equation (6.6). The objective function consists of fixed costs, transport costs, operational costs, penalty costs and potential revenue as is shown in equation (6.7) – equation (6.11), respectively. Equation (6.7) represents the fixed costs of the location opening of TDWCSCs, TDWPRCs, and landfills and the investing RSR technology at each TDWPRC. Equation (6.8) represents the transport cost through the supply chain network. Equation (6.9) represents the operational cost of TDWCSCs, TDWPRCs, and the landfills. Equation (6.10) represents the penalty costs for activities with environmental impacts that are related to the transport process and the operational process. Equation (6.11) represents the potential revenue incurred from saleable waste obtained from the TDWCSCs and TDWPRCs. Equation (6.12) – equation (6.14) state that the total number of selected locations cannot exceed the maximum limit of each location type, equation (6.12) enforces the limit of selected TDWCSCs, equation (6.13) enforces the limit of selected TDWPRCs and equation (6.14) enforces the limit of selected landfills. Equation (6.15) – equation (6.18) limits the volume of debris assigned to each location type. Equation (6.15) ensures that the volume of debris assigned to TDWCSC cannot exceed the maximum capacity of each TDWCSC. Equation (6.16) limits the volume of debris assigned to TDWPRC according to the RSR technology capacity available at the TDWPRC. Equation

(6.17) requires that a TDWPRC must be opened in order to make RSR technologies available. Equation (6.18) ensures that the volume of debris assigned to the landfill cannot exceed the maximum capacity of each landfill. Equation (6.19) guarantees that the volume of debris in each affected zone is collected and processed. Equation (6.20) – equation (6.22) state that all collected debris in each selected TDWCSC is transported to processing sites (TDWPRC), landfills and markets. Equation (6.23) and equation (6.24) state that the debris in each selected TDWPRC is transported to landfills and markets. To protect against bafflement of the assignment, this study provides conditions according to the above assumptions, the conditions are represented as equation (6.25) – equation (6.29). Equation (6.25) provides that each affected zone can be served by one node from TDWCSC or TDWPRC. Equation (6.26) provides that the waste from each TDWCSC that needs to be treated with each RSR technology can be served by one TDWPRC. Equation (6.27) – equation (6.28) provide that each TDWCSC can be served by one landfill and one market. Equation (6.29) provides that each TDWPRC can be served by one market. Equation (6.30) – equation (6.35) state that the binary variable of the assignment is set to 1 when the volume of debris in each node is assigned to each node. Lastly, equation (6.36) – equation (6.37) describe non-negativity and the binary conditions of the decision variables.

The solution of the proposed mathematical model is reached with consideration of the number of TDWCSCs, TDWPRCs, and landfills, the allocation of each node, the total planning budget, the penalty of environmental and human effects and the revenue from any sellable waste that can be calculated. Owing to an integrated model of on-site and off-site separation for recyclable materials, this can balance the benefits of both approaches such as those associated with recycling rates, recycling costs, revenues, logistics, management of information resource availability and any environmental and human effects [17]. This result can serve emergency management purposes. The first is to help in the preparation stage and includes the spatial distribution of waste collection and separation sites, processing and recycling sites, and disposal sites, assignment of waste in each affected community, and the expectations of the planning budget. The second is to aid in the recovery stage in order to provide debris flow and directions at each step of the post-disaster waste supply chain management process and to reduce the effects on humans and the environment in the post-disaster supply chain network as well.

6.4 Solution algorithm

This chapter aims to find the post-disaster waste supply chain management plan under a minimum standard of total costs incurred in the supply chain. According to the problems associated with the NP-hard system, the solution cannot be found by mathematical programming solution software when a larger problem is presented. In the actual practice, the decision made on the operation for facility location and allocation in the PWSCM problem involves an evaluation of a variety of scenarios including a range of possible data employed to reach an acceptable solution. In the model, the computation time involves a lengthy amount ot time to reach a solution and this is not desirable in practice. Therefore, we aim to propose a solution algorithm by using a metaheuristic approach. The detail of the encoding and decoding scheme, allocation solution and local search for PWSCM problem are shown as follow:

6.4.1 Encoding and decoding scheme

A. Encoding

The encoding procedures used in this study starts from providing the number of dimensions that are made up of the dimensions of the maximal number of selected locations in each location type, the sequence of location selection in each location type, and the sequence of assignment for allocation. The total dimensions can be calculated as 3+I+3J+2K+L where I is the number of affected zones, J is the number of TDWCSCs, K is the number of TDWPRCs and L is the number of landfill sites. To more easily understand, this considers an example with two locations in each location type and two RSR technologies. For this example, the number of dimensions is equal to 17. The Figure 6.5 illustrates an encoding scheme of a random key representation in which each value in a dimension is randomly generated with a uniform random number (RN) between 0 and 1. The dimensions are separated into seven sets as are shown in Figure 6.5 The set 1 – 4 are used to generate the open/close decision of each location type, while the set 5 – 7 are used in allocation method.

B. Decoding

To decode the random numbers in a dimension of this problem, a sorting list rule is applied in this study. The example of decoding methods is represented in Figure 6.6. The Figure 6.6 (a) presents the decoding example for the maximal number of selected location in Set 1, while The Figure 6.6 (b) illustrates the decoding example for the sequence of location selection and the sequence of the assignment for allocation in Set 2 – 7.

As shown in the Figure 6.6 (a), the example of the decision for the maximal number of selected TDWPRCs is represented. The maximal number of selected location is identified using a sorting rule with a choice of the maximal number of selected location. The choice for the maximal number of selected location can be calculated as U+1, where U is the total numbers of location that can be selected from the candidate location. In this example, we assume that the U value is two in each location type. Since there are three choices to make the decision for TDWPRC in this example problem, three choices have equally ranged under the space between 0 and 1. So, each choice can be selected with the probability of 1/3. According to the random value of the maximal number of selected TDWPRCs in Figure 6.5 is 0.41, the random value is taken between 0.33 – 0.67. Therefore, the decoding solution for the maximal number of selected TDWPRCs is provided as 1. For the decision on the maximal number of selected TDWCSCs and landfill sites in Set 1 can be decoded in the same way.

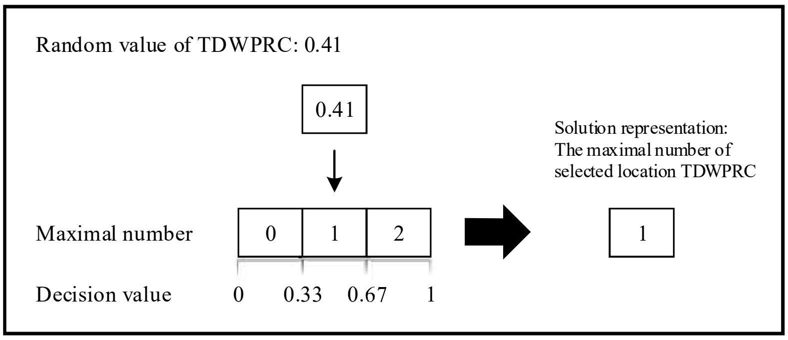
To generate the sequencing in Set 2-7, the decoding example for the sequence of TDWPRC selection (Set 3) is proposed in Figure 6.6 (b). The sequence is determined according to the order of ascending values in a dimension, in which this means that the sequence is ordered from the minimum random number to the maximum random number. The solution of example for the sequence of TDWPRC selection in Figure 6.6 (b) showed that the TDWPRC 1 is determined as a sequence number 2 while the TDWPRC 2 is provided as a sequence number 1. The same procedure is applied to decode the sequencing in Set 2-7. After both decoding approaches are applied to this problem, the summary of all solution representations can be illustrated in Figure 6.7.

Dimension No. *d*

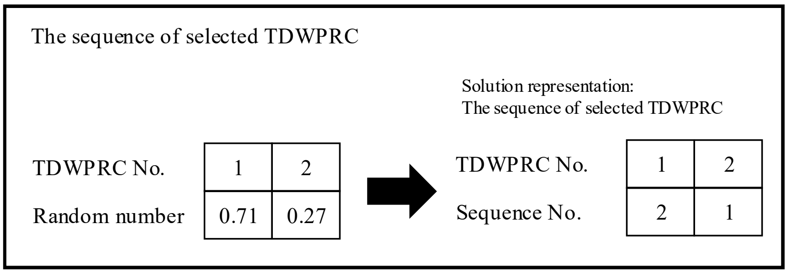
Dim.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
RN	0.73	0.41	0.48	0.34	0.54	0.71	0.27	0.56	0.20	0.35	0.64	0.98	0.77	0.24	0.85	0.31	0.52
									⇓								
Set	Set 1			Set 2		Set 3		Set 4		Set 5		Set 6		Set 7			
Name	The maximal number of selected			Sequence of TDWCSC selection		Sequence of TDWPRC selection		Sequence of landfill site selection		Sequence of affected zone assignment		Sequence of TDWCSC assignment for transferring to TDWPRC		Sequence of TDWCSCs and TDWPRC assignment for transferring to landfill and market			
	TDWCSCs (MJ)	TDWPRCs (MK)	Landfill sites (ML)														

Open/close decision (Dim. 1–9) — Allocation decision (Dim. 10–17)

Figure 6.5 An encoding scheme for PWSCM system



(a)



(b)

Figure 6.6 An example of decoding scheme
(a) A decoding for the maximal number of selected TDWPRC;
(b) A decoding for the sequence of TDWPRC selection.

Dim.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Location type	The maximal number of selected			TDWCSC		TDWPRC		Landfill site		Affected zone		TDWCSC		TDWCSC		TDWPRC	
ID No.	MJ	MK	ML	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Decode	2	1	1	1	2	2	1	2	1	1	2	2	1	1	4	2	3
	The maximal number of selected location (Set 1)			Sequence of TDWCSC selection (Set 2)		Sequence of TDWPRC Selection (Set 3)		Sequence of landfill site selection (Set 4)		Sequence of affected zone assignment (Set 5)		Sequence of TDWCSC assignment for transferring to TDWPRC (Set 6)		Sequence of TDWCSCs and TDWPRC assignment for transferring to landfill and market (Set 7)			

Figure 6.7 The summary of decoding scheme for PWSCM system

Location type	TDWCSC 1	TDWCSC 2	TDWPRC 1	TDWPRC 2	Landfill 1	Landfill 2
Open/Close	1	1	0	1	0	1

Figure 6.8 An open/close decision of each location type.

To identify the open/close decision of each location type, the decoding in set 1 – 4 is employed for making a decision. The selected method in each location type is generated following the sequence of the location selection along with the maximal number of selected locations. If the sequence number of facility location is less than or equal to the maximal number of selected location, that facility location is selected to open. Otherwise, that facility location is determined to close. The solution of open/close decision in this example is represented as shown in Figure 6.8. As is illustrated in Figure 6.8, the TDWCSC 1, TDWCSC 2, TDWPRC 2, and Landfill site 2 are opened, while the remaining locations are closed. Note that the value 1 is "open" and the value 0 is "closed".

6.4.2 Allocation solution

After the decisions on location selection (Open/Close) and the sequence of assignment at each stage is made, the method of allocation of PWSCM is proposed. The structure of method is divided into three main stages: (1) allocating waste for collection and separation; (2) allocating waste for processing and recycling; (3) allocating waste for disposal and sale. At each step in each stage, only one arc is added to the system by selecting an origin location with the highest priority and connecting it to a destination location considering the minimum total cost of transport and operation (*LC*). The decoding in set 5 – 7 is employed to determine the priority of allocation in which the priority is sequenced from the minimal sequence number to the maximal sequence number. The available locations in each location type are considered following the decoding scheme of open/close decision. The pseudo code of allocation method is described as follows.

Stage 1: Allocating waste for collection and separation
The allocation algorithm is initiated from this stage. All affected zones are assigned to the location of collection and separation. To consider the separation method of recyclable materials, the on-site and off-site separation are determined at this stage. Some affected zones are provided to separate on-site while the rest goes to an off-site separation facility. The decoding in set 5 is employed to determine the priority of allocation in this stage. The pseudo code of this stage is listed in Table 6.3.

Stage 2: Allocating waste for recycling
After the allocation of waste for collection and separation is completed, the process of allocating waste for recycling is then proposed for the next step. This stage operates for processing and recycling by considering RSR technologies. The waste at TDWCSC is allocated to TDWPRC by separating the debris for each RSR technology, while the waste that is separated at the off-site (TDWPRCs) do not need to make the allocation. To make the sequence of allocation for TDWCSCs, the decoding in set 6 is applied. The pseudo code of this stage is listed in Table 6.4.

Stage 3: Allocating waste for disposal and sale
Finally, allocation of waste for disposal and sale is proposed. The decoding in set 7 is applied for determining the priority of TDWCSCs and TDWPRCs allocation in this stage. In this stage, the waste at the TDWCSCs and TDWPRCs is divided into two portions; disposal and sale. The waste is then assigned to landfill sites and markets, respectively. The pseudo code of this stage is listed in Table 6.5.

Table 6.3 Pseudo code of phase 1

```
Input:    H_i, C_j^{TDWCSC}, C_kn^{RSR}, Ca_ij, Cb_ik, O_j^{TDWCSC}, O_kn^{TDWSRC}, v(i)
Output:   a_ij, b_ik
Begin
    Set a_ij ← 0, b_ik ← 0, ∀i ∈ I, ∀j ∈ J, ∀k ∈ K
    Repeat
    Select affected zone i with the sequence of affected zone assignment by priority-based decoding; i ← arg min { v(i)}
    Set LC ← MaxValue, nj
        Do
        Repeat
        Check the status (Open/Close) and capacity of the TDWCSC j
        Determine the cost of transportation and operation between affected zone i and TDWCSC j, Ca_ij + O_j^{TDWCSC};
          LC ← min {Ca_ij + O_j^{TDWCSC}, i ∈ I, j ∈ J,}; update the total cost of allocation
          nj ← arg min {Ca_ij + O_j^{TDWCSC}, i ∈ I, j ∈ J,}; update the node of allocation
        Until the last TDWCSC
        Repeat
        Check the status (Open/Close) and capacity of the TDWPRC k for recycling by RSR technology n
        Determine the cost of transportation and operation between affected zone i and TDWPRC k, Cb_ik + O_kn^{TDWSRC};
          LC ← min {Cb_ik + O_kn^{TDWSRC}, j ∈ J, k ∈ K, n = 1}; update the total cost of allocation
          nk ← arg min {Cb_ik + O_kn^{TDWSRC}, j ∈ J, k ∈ K, n = 1}; update the node of allocation
        Until the last TDWPRC
        Selected lowest cost node, then allocate the waste of affected zone i to destination and update capacity of TDWCSCs
        and TDWPRCs
        End do
    Output a_ij and b_ik
    Until the last affected zone
End
```

Table 6.4 Pseudo code of phase 2

```
Input:    a_ij, C_kn^{RSR}, Cc_jk, O_kn^{TDWSRC}, γ_n, v(i)
Output:   c_jkn
Begin
    Set c_jkn ← 0, ∀j ∈ J, ∀k ∈ K
    Repeat
    Select TDWCSC j with the sequence of TDWCSC assignment by priority-based decoding; j ← arg min { v(i)}
        Repeat
        Set LC ← MaxValue, nk
        Consider the RSR technology n
        Calculate the proportion of debris from TDWCSC j that is eligible to be treated with RSR technology n; base on
        Equation (6.15)
            Do
            Repeat
            Check the status (Open/Close) and capacity of the TDWPRC k that needs to be treated with RSR technology
            n
            Determine the cost of transportation and operation between TDWCSC j and TDWPRC k, Cc_jk + O_kn^{TDWSRC};
              LC ← min {Cc_jk + O_kn^{TDWSRC}, j ∈ J, k ∈ K, n = 2 … N}; update the total cost of allocation
              nk ← arg min {Cc_jk + O_kn^{TDWSRC}, j ∈ J, k ∈ K, n = 2 … N}; update the node of allocation
            Until the last TDWPRC
            Selected lowest cost node, then allocate the waste of TDWCSC j for recycling by technology n to TDWPRC
            k and update capacity of TDWPRCs
            End do
        Output c_jkn
        Until the last RSR technology
    Until the last TDWCSC
End
```

Table 6.5 Pseudo code of phase 3

Input: b_{ik} ,c_{jkn}, γ_n, η_n, ρ_n, $O_l^{Landfill}$, $C_l^{Landfill}$, δ_m, Cd_{jl}, Ce_{jm}, Cf_{kl}, Cg_{km}, $v(i)$
Output: d_{jl}, e_{jm}, f_{kl}, g_{km}
Begin
Set $d_{jl} \leftarrow 0$, $e_{jm} \leftarrow 0$, $f_{kl} \leftarrow 0$, $g_{km} \leftarrow 0$, $\forall j \in J$, $\forall k \in K$,$\forall l \in L$, $\forall m \in M$,
Repeat
Select TDWCSC j or TDWPRC k with the sequence of TDWCSCs and TDWPRCs assignment for transferring to landfill and market by priority-based decoding; $t \leftarrow$ arg min $\{ v(j+k)\}$
If $t \in J$, **then**
Calculate the proportion of debris from TDWCSC j that needs to be assigned to landfills and markets.
Do
Set $LC \leftarrow MaxValue, nl$
Repeat
Check the status (Open/Close) and capacity of the landfill l
Determine the cost of transportation and operation between TDWCSC j and landfill l, $Cd_{jl} + O_l^{Landfill}$;
$LC \leftarrow$ min $\{Cd_{jl} + O_l^{Landfill}, j \in J, l \in L\}$; update the total cost of allocation
$nl \leftarrow$ arg min $\{Cd_{jl} + O_l^{Landfill}, j \in J, l \in L\}$; update the node of allocation
Until the last landfill
Selected lowest cost node, then allocate the waste of TDWCSC j for disposal to landfill l and update capacity of landfill l
Set $LC \leftarrow MaxValue, nm$
Repeat
Determine the cost of transportation and operation between TDWCSC j and market m, $Ce_{jm} + \delta_m$;
$LC \leftarrow$ min $\{Ce_{jm} + \delta_m, j \in J, m \in M\}$; update the total cost of allocation
$nm \leftarrow$ arg min $\{Ce_{jm} + \delta_m, j \in J, m \in M\}$; update the node of allocation
Until the last market
Selected lowest cost node, then allocate the waste of TDWCSC j for sale to market m and update capacity of market m
End do
else
Calculate the proportion of debris from TDWPRC k that needs to be assigned to landfills and markets.
Do
While (**not** terminating condition) **do**
Set $LC \leftarrow MaxValue, nl$
Repeat
Check the status (Open/Close) and capacity of the landfill l; $C_l^{Landfill} > 0$
Determine the cost of transportation and operation between TDWPRC k and landfill l, $Cf_{kl} + O_l^{Landfill}$;
$LC \leftarrow$ min $\{Cf_{kl} + O_l^{Landfill}, k \in K, l \in L\}$; update the total cost of allocation
$nl \leftarrow$ arg min $\{Cf_{kl} + O_l^{Landfill}, k \in K, l \in L\}$; update the node of allocation
Until the last landfill
Selected lowest cost node, then allocate the waste of TDWPRC k for disposal to landfill l and update capacity of landfill l; $f_{kl}^* \leftarrow$ min $\{f_{kl}^*, O_l^{Landfill*}\}$
End
Set $LC \leftarrow MaxValue, nm$
Repeat
Determine the cost of transportation and operation between TDWPRC k and market m, $Cg_{km} + \delta_m$;
$LC \leftarrow$ min $\{Cg_{km} + \delta_m, k \in K, m \in M\}$; update the total cost of allocation
$nm \leftarrow$ arg min $\{Cg_{km} + \delta_m, k \in K, m \in M\}$; update the node of allocation
Until the last market
Selected lowest cost node, then allocate the waste of TDWPRC k for sale to market m and update capacity of market m
End do
Output d_{jl}, e_{jm}, f_{kl}, g_{km}
Until the last assignment
End

6.4.3 Local search

In general, a local search may be applied to a certain group of vectors or particles in order to enhance the exploitation of the search space. The local search typically attempts to improve the quality of the solution by searching for better solutions around its neighbors. According to the above solution, some facility locations do not need to be opened with full capacity.

Therefore, the local search is proposed to improve the quality of the solution by providing the maximum capacity of each location. The encode and decode are presented as Figure 6.9. In this study, the TDWCSC and TDWPRC are provided to find the maximum capacity of each location in order to improve the quality of the solution since those factors are able to threaten the next generated stage in finding better or worse solutions.

Dimension No. λ

Dim.	1	2	3	4	5	6
RN	0.73	0.41	0.98	0.34	0.54	0.61

(a)

⇓

Dim.	1	2	3	4	5	6
Facility type	TDWCSC 1	TDWCSC 1	TDWPRC 1 with RSR 1	TDWPRC 1 with RSR 2	TDWPRC 2 with RSR 1	TDWPRC 2 with RSR 1
Capacity	8000	6000	10000	4000	6000	8000

(b)

Figure 6.9 Example of solution representation of local searches: (a) An encoding scheme, (b) A decoding scheme,

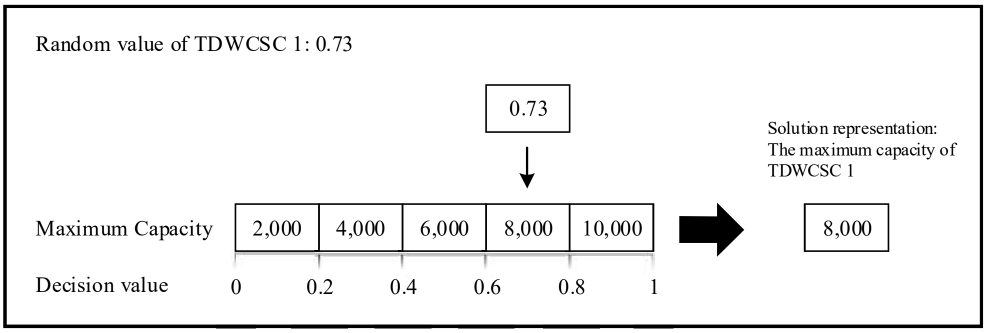


Figure 6.10 A decoding example of TDWCSC 1 under the portion of capacity associated with the decision value.

According to this example considers two locations in each location type and two RSR technologies. The dimensions of local search are set at 6 (J+(K×N)), where J is the number of TDWCSCs, K is the number of TDWPRCs and N is the number of RSR technologies. The encoding value in the dimensions is generated with a uniform random number between [0,1]. To decode the dimension of this problem, a sorting list rule is applied to an individual value to generate the maximum capacity. Assume that the portion of capacity in this example is separated with a probability of 1/5 and the capacity of each location type and RSR technology type is provided as 10,000. According to those mentions, the portion of capacity associated with the decision value and the example of TDWCSC 1 can be represented as Figure 6.10. In this example, the random number of TDWCSC 1 is 0.73 fall between 0.6-0.8. Hence, the capacity of TDWCSC 1 is adjusted to be 8,000. The same procedure is employed to decode the capacity in each location. According to the random number in Figure 6.9(a), the solution representation of the decoding process is illustrated in Figure 6.9(b). After the maximum capacity is provided, the solution is improved using the proposed algorithm. If the fitness value is improved and made better than the previous solution, then the new solution and the new fitness value are updated.

6.5 Computational experiments

6.5.1 Parameter setting and test problems

The performance of the metaheuristic algorithms does not only depend on the searching mechanisms and solution representation procedures, but the parameter setting also affects how good the solutions are and how they can be found and converged [30]. In this study, two metaheuristic approaches are proposed to solve the PWSCM problem; the Differential Evolution (DE) and Particle Swarm Optimization (PSO). In both algorithms, the function evaluations are set as a fixed value of 300,000, so that sufficient function evaluations are allowed in order to find the best solution. To determine the appropriate parameters of PSO and DE; firstly, the preliminary experiments are conducted with four different values of each parameter. Then, for each parameter, while the values of the other parameters are fixed, the two best parameter values out of all the other parameter values are identified according to the total cost obtained from the algorithm. The following combinations of the parameter's two suitable values are further tested for each size of the specified instance.

A full factorial design is conducted to determine the best parameter setting as is shown in Table 6.6. The average results obtained from the algorithm are then computed for each parameter setting. The decision-making process and the statistical approach are considered according to the results and they are employed to identify the suitable parameters. The results indicate that the best solution quality is obtained from the parameter setting as is shown in Table 6.7. Hence, this method will be used in the following computational study.

Table 6.6 Parameter experiments

PSO	DE
Swarm size: 150, 200	Population size: 150, 200
w: [0.1, 0.5], [0.4, 0.9] (lineally increase)	F: [0.1, 0.5], [0.5, 1] (linearly increase)
c_p: 1, 1.6	C_r: [0.1, 0.5], [0.5, 1] (linearly increase)
c_g: 1, 1.6	

Table 6.7 Parameter setting

PSO		DE	
Number of iterations	1500	Number of iterations	2000
Number of particles	200	Number of population	150
Inertia weight, w	[0.4, 0.9]	Amplification factor, F	[0.1, 0.5]
Personal best position, c_p	1	Crossover rate, C_r	[0.5, 1]
Global best position, c_g	1		

6.5.2 Experimental results

The experiments of PWSCM are implemented using C# language of Microsoft Visual Studio 2015. A personal computer with an Intel(R) Xeon(R) X5690 CPU @ 3.47GHz with 24GB RAM is used to execute and verify the algorithms. To determine the performance of PSO and DE, LINGO 16 is proposed to evaluate the algorithm solution. The numerical results obtained from the PSO and DE are compared with an optimal solution and the PSO and DE are compared under the same conditions which are the encoding and decoding schemes. The Gap of the solution (*Gap*) obtained from the PSO or DE versus LINGO software solver and the Relative Improvement (*RI*) of the solution obtained from the PSO versus DE is evaluated according to Equation 6.38 and Equation 6.39, respectively.

$$Gap = ((Sol_{PSOorDE} - Sol_{LINGO}) / Sol_{LINGO}) \times 100 \tag{6.38}$$

$$RI = ((Sol_{DE} - Sol_{PSO}) / Sol_{DE}) \times 100 \tag{6.39}$$

where *Gap* = the gap of solution (%) between proposed algorithm solution by using PSO or DE and optimal solution*,

RI = the relative improvement between Sol_{PSO} and Sol_{DE}**

Sol_{PSO} = the solution of proposed algorithm obtained from PSO,

Sol_{DE} = the solution of proposed algorithm obtained from DE,

Sol_{Lingo} = the optimal solution obtained from LINGO software solver.

Note

*The more positive *RI* is the superior performance of PSO to the DE,

**The more negative *Gap* is the superior performance of PSO or DE to the LINGO software solver.

In this study, twenty PWSCM problems were generated for evaluation with respect to the number of the affected zones (I), TDWCSC (J), TDWPRC (K), landfills (L), markets (M) and RSR technology (N) and are shown in Table 6.8. The number of variables (integers) and constraints of the smallest size problem was at 153 (70) and 121, while the number of variables (integers) and constraints of the largest size problem was at 373,375 (184,445) and 188,104, as is shown in Table 6.8. Although the optimal solutions were not available within 12 hrs (43200s) of computational time, the best feasible solution found in the limited time given was set to be compared with the one obtained through the proposed algorithm from PSO and DE. In some cases, the feasible solution from LINGO could not be found within 12 hrs (43200s). Therefore, the comparison of the gap in some cases will not be found. Various instances were designed to investigate how the performance of the proposed algorithm works for real cases. The PWSCM problem was tested with two case groups; without a limit of locations and with a limit of locations. Some data have been referenced from the work of Fetter and Rakes (2012) such as the volume of debris, reduction proportion, proportion of reduced debris from RSR technology saleable as recycled material, cost of RSR technology, disposal cost, and revenue. Tables 6.9 and 7.10 show the results of the PWSCM problem without a limit of locations and with a limit of locations such as the optimal (feasible) solution within the computational time limit, the best, average and standard deviations of the total cost of PWSCM from ten runs of each algorithm for each case, the gap of the solution and the RI of the best and average solutions obtained from the PSO and DE. Moreover, a comparison of the total cost in the supply chain between LINGO software solver, PSO, DE and RI between PSO and DE is illustrated in Figure 6.11 and Figure 6.12, respectively.

Table 6.8 Experimental design for various cases

Case	Test problem						Variables		St.
	I	J	K	L	M	N	Total	Integers	
1	10	2	2	2	2	2	153	70	121
2	15	3	3	2	2	3	320	152	233
3	20	3	4	3	2	2	437	205	291
4	32	4	4	4	3	3	772	368	497
5	40	7	5	5	4	3	1,454	700	877
6	50	10	5	5	5	3	2,175	1,060	1,284
7	64	10	8	5	5	3	3,240	1,579	1,846
8	70	15	10	8	6	4	5,547	2,696	3,067
9	80	18	12	9	9	4	7,784	3,783	4,222
10	96	20	15	10	8	3	9,958	4,830	5,286
11	100	20	10	5	10	3	8,235	4,065	4,504
12	123	25	15	10	8	3	13,718	6,710	7,265
13	208	32	10	10	10	4	21,901	10,848	11,685
14	325	40	18	13	12	3	45,169	22,351	23,460
15	427	47	20	18	15	4	69,490	34,385	35,885
16	500	50	30	20	20	3	95,775	47,290	48,899
17	632	60	30	30	30	4	139,445	68,820	70,933
18	785	65	25	30	27	4	165,010	81,750	84,484
19	890	78	32	36	30	5	235,895	116,794	119,821
20	1000	100	50	45	30	5	373,375	184,445	188,104

Table 6.9 Experimental results of total costs in supply chain network on a set of generated problems for PWSCM problem without a limit of facility location

Case	LINGO	Time(s)	PSO			Time(s)		Gap	DE			Time(s)		Gap		RI PSO V.S. DE	
			Best	Avg.	SD	Max	Avg.		Best	Avg.	SD	Max	Avg.			Best	Avg.
1	2,248,082	0.12	2,248,082	2,248,082	0	9.23	8.70	0.00	2,248,082	2,248,082	0	6.91	6.63	0.00		0.000	0.000
2	4,147,719	0.19	4,147,719	4,197,464	28,790	16.58	15.85	0.00	4,154,247	4,201,890	20,055	10.45	9.54	0.16		0.157	0.105
3	4,700,234	0.26	4,717,774	4,770,161	29,154	19.17	15.73	0.37	4,743,637	4,778,167	23,617	10.91	10.03	0.92		0.548	0.168
4	7,869,143	4.91	7,966,519	7,971,479	9,921	21.66	20.19	1.24	7,966,519	7,976,440	12,151	12.10	10.60	1.24		0.000	0.062
5	9,761,045	46.31	9,991,247	10,002,143	16,301	32.87	30.48	2.36	9,991,247	9,991,539	238	19.19	17.41	2.36		0.000	-0.106
							Avg.	0.79					Avg.	0.94	Sum	0.706	0.230
6	11,231,379	26.70	11,389,372	11,396,028	19,259	68.81	49.23	1.41	11,389,372	11,389,372	0	27.51	26.14	1.41		0.000	-0.058
7	15,100,348	59.24	15,131,298	15,156,036	14,878	142.37	109.38	0.20	15,131,298	15,137,134	3,112	52.95	46.65	0.20		0.000	-0.125
8	15,763,198	11.97	15,919,309	15,941,996	18,609	196.40	156.33	0.99	15,919,309	15,946,133	18,347	86.56	72.43	0.99		0.000	0.026
9	17,838,085	329.57	17,932,287	17,954,250	18,880	283.89	197.57	0.53	17,932,287	17,947,596	12,979	105.48	95.98	0.53		0.000	-0.037
10	20,317,408	4,800.40	20,455,602	20,487,863	33,173	419.70	389.98	0.68	20,451,317	20,467,015	14,887	250.21	167.53	0.66		-0.021	-0.102
							Avg.	0.76					Avg.	0.76	Sum	-0.021	-0.296
11	22,627,670	568.39	22,722,402	22,734,780	8,236	319.84	278.16	0.42	22,724,201	22,748,009	21,474	187.56	138.72	0.43		0.008	0.058
12	26,093,300	*	26,289,751	26,367,311	52,167	605.91	550.57	0.75	26,277,343	26,330,763	28,610	236.78	195.35	0.71		-0.047	-0.139
13	48,913,284	*	49,569,429	49,675,117	65,696	518.06	491.83	1.34	49,616,613	49,699,993	48,057	293.57	260.35	1.44		0.095	0.050
14	52,615,345	*	52,955,126	53,054,256	71,640	2267.63	1551.38	0.65	52,914,825	53,058,966	96,266	1156.65	834.72	0.57		-0.076	0.009
15	77,022,030	*	77,850,798	78,097,400	113,518	4161.66	2318.99	1.08	78,067,804	78,131,755	49,129	1257.37	1150.33	1.36		0.279	0.044
							Avg.	0.85					Avg.	0.90	Sum	0.259	0.023
16	82,064,060	*	81,948,577	82,102,085	77,124	6429.49	4698.04	-0.14	81,982,681	82,113,771	84,580	3828.86	2863.43	-0.10		0.042	0.014
17	121,308,516	*	114,119,072	114,184,771	42,050	5632.94	5397.10	-5.93	114,120,154	114,187,495	48,648	3186.78	2979.96	-5.93		0.001	0.002
18	157,454,091	*	144,331,371	144,559,635	255,375	5988.12	4386.87	-8.33	144,772,211	144,983,525	130,340	2784.12	1627.94	-8.05		0.305	0.293
19	N/A	*	171,946,226	172,317,432	178,949	5497.75	5011.51	N/A	173,021,584	173,127,012	77,277	3321.10	2108.60	N/A		0.625	0.470
20	N/A	*	184,017,153	184,110,265	60,840	23112.97	22843.68	N/A	184,039,379	184,224,530	166,896	17669.26	15648.61	N/A		0.012	0.062
							Avg.	-4.80					Avg.	-4.69	Sum	0.985	0.842

*indicates that the best solution found was in 12 hours (43,200 s), while the optimal solution was not available

Table 6.10 Experimental results of total costs in supply chain network on a set of generated problems for PWSCM problem with a limit of facility location.

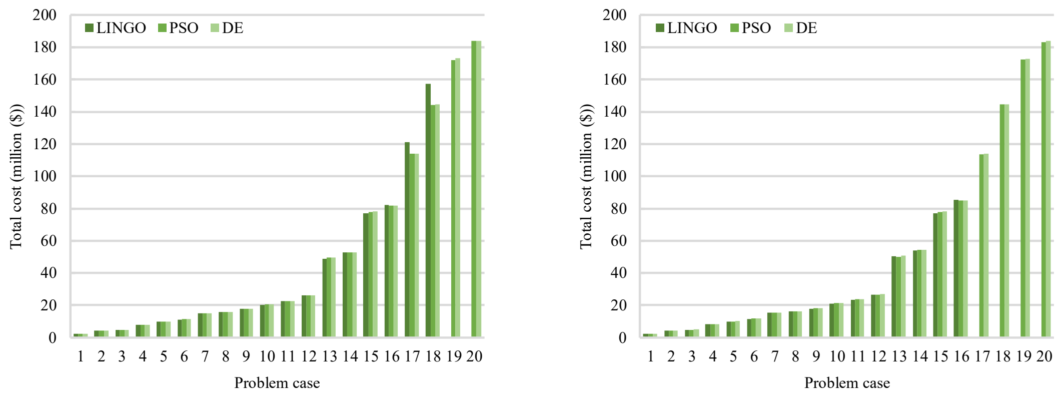
Case	LINGO	Time(s)	PSO			Time(s)		Gap	DE			Time(s)		Gap		RI PSO V.S. DE	
			Best	Avg.	SD	Max	Avg.		Best	Avg.	SD	Max	Avg.			Best	Avg.
1	2,287,871	0.11	2,287,871	2,287,871	0	8.36	7.02	0.00	2,287,871	2,287,871	0	5.27	5.08	0.00		0.000	0.000
2	4,248,466	0.22	4,248,466	4,261,580	6,557	13.43	10.12	0.00	4,248,466	4,262,005	5,785	7.75	6.39	0.00		0.000	0.010
3	4,778,515	0.33	4,781,516	4,869,678	57,459	14.96	11.43	0.06	4,906,223	4,914,580	2,786	6.99	6.77	2.67		2.608	0.922
4	8,261,991	10.81	8,320,360	8,411,137	114,629	21.23	18.87	0.71	8,381,368	8,466,295	71,490	10.98	9.77	1.44		0.733	0.656
5	9,855,092	170.93	10,005,681	10,116,301	82,833	19.62	19.21	1.53	10,127,872	10,504,335	203,566	10.98	9.19	2.77		1.221	3.836
							Avg.	0.46					Avg.	1.38	Sum	4.563	5.424
6	11,463,659	99.24	11,718,222	11,798,881	91,419	40.45	36.64	2.22	11,718,222	11,721,883	5,837	21.42	16.82	2.22		0.000	-0.653
7	15,467,488	43,200.00	15,467,545	15,528,214	44,627	62.04	58.04	0.00	15,484,260	15,541,952	37,362	38.14	34.54	0.11		0.108	0.088
8	16,249,516	413.49	16,360,544	16,519,496	138,376	39.79	31.50	0.68	16,378,618	16,627,432	127,791	20.26	19.07	0.79		0.110	0.653
9	17,904,998	910.23	18,085,518	18,278,828	86,901	53.95	49.05	1.01	18,231,508	18,571,328	273,463	23.71	17.70	1.82		0.807	1.600
10	20,917,017	7,440.47	21,314,826	21,500,924	106,779	84.88	69.80	1.90	21,385,088	21,547,541	207,489	45.07	33.80	2.24		0.330	0.217
							Avg.	1.16					Avg.	1.44	Sum	1.355	1.906
11	23,440,007	*	23,668,575	23,797,760	107,535	120.29	118.75	0.98	23,699,489	23,785,861	96,221	75.93	67.64	1.11		0.131	-0.050
12	26,398,570	*	26,728,440	27,022,953	244,048	80.40	65.06	1.25	26,890,925	27,376,307	283,091	39.79	26.38	1.87		0.608	1.308
13	50,450,854	*	50,115,669	50,656,224	257,111	109.71	89.03	-0.66	50,985,276	51,854,275	611,930	38.97	24.38	1.06		1.735	2.365
14	54,039,564	*	54,365,664	54,666,788	166,186	758.13	719.99	0.60	54,502,530	54,885,033	243,656	423.19	342.99	0.86		0.252	0.399
15	77,029,993	*	77,817,591	78,120,094	116,484	1622.43	1449.33	1.02	78,060,828	78,428,764	130,129	596.84	527.80	1.34		0.313	0.395
							Avg.	0.64					Avg.	1.25	Sum	3.038	4.417
16	85,378,377	*	85,015,474	85,215,109	165,296	858.74	722.76	-0.43	85,135,823	86,117,567	1,059,144	691.52	626.78	-0.28		0.142	1.059
17	N/A	*	113,711,350	113,977,700	163,811	2631.92	2543.34	N/A	114,064,853	114,389,559	225,613	1595.46	1215.63	N/A		0.311	0.361
18	N/A	*	144,412,521	144,582,565	128,279	2848.63	2651.79	N/A	144,601,319	145,158,103	239,175	2354.22	1883.26	N/A		0.131	0.398
19	N/A	*	172,408,347	172,692,499	181,971	4119.55	3655.57	N/A	172,622,228	173,407,216	316,328	5024.26	2622.45	N/A		0.124	0.414
20	N/A	*	183,205,084	183,769,445	210,504	10167.94	9138.07	N/A	183,915,996	184,679,456	280,664	7965.27	5776.45	N/A		0.388	0.495
							Avg.	-0.43					Avg.	-0.28	Sum	1.095	2.728

*indicates that the best solution was found in 12 hours (43,200 s), while the optimal solution was not available

According to the results from Table 6.9 and Table 6.10, the differences between the global optimum figures of the LINGO software and the proposed algorithm using PSO and DE are sufficiently small. When the results of the PWSCM problem without a limit of locations are reviewed as is shown in Table 6.9 and Figure 6.11 (a), the maximum gap of 2.36%, as the difference from the global optimum, is admissible in persuading the acceptability of the proposed algorithms' performance. While LINGO software could not find the solution within a reasonable computing time (12 h), as the problem size increases, PSO and DE showed their potential in solving the larger problems (case 19-20) without difficulties.

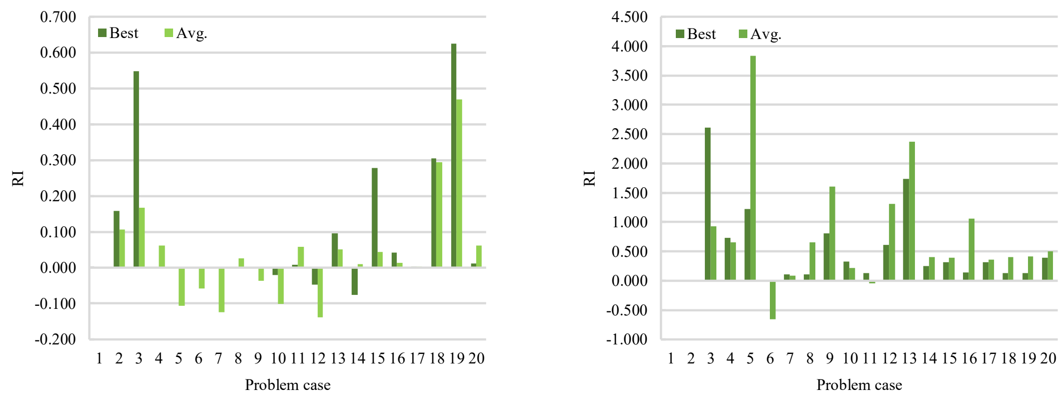
The performance of the LINGO software overcame the PSO and DE, while in many cases it took more time than the proposed algorithm that used PSO and DE. In the very large- size problem (case 16-20), the proposed algorithm using PSO and DE found a preferred solution to what the LINGO software was able to find. The performance values of the proposed algorithm using PSO were 0.8% away in average according to the optimal solution for the small (case 1-5), medium (case 6-10) and large (case 11-15) sized problems, while the performance values from DE were 0.87% away in average. The average of the very large-sized problem from PSO was -4.80, while the DE was -4.69. To compare the degree of performance of PSO and DE, the results of the RI are shown in Figure 6.12 (a). In some cases, the DE was able to find the best solution and better average solution than the PSO. However, the PSO also displays the outstanding performance of the DE when compared with all of the cases. In the results of the PWSCM problem with the limit of locations, as is shown in Table 6.10 and Figure 6.11 (b), the maximum error of both algorithms obtained from the global optimum was 2.22% and 2.77%, respectively. In this case, the LINGO software was able to find the optimal solution in small- and medium-sized problems (except in case 7). The average gap between the optimal solution and the proposed algorithm using the PSO of the small- and medium-sized problems was 0.46% and 1.03%, respectively. While the average gap between the optimal solution and the proposed algorithm using the DE of the small- and medium-sized problems was 1.38% and 1.44%, respectively. In the large-sized problem, the LINGO software was still able to find the solution, but it was not an optimal solution. However, the LINGO software also yielded a better solution than the proposed algorithms using PSO and DE in which the gap of the PSO was 0.64%, while the gap of the DE was 1.25%. When the very large-sized problems are tested, the results of the very large-sized problem using the LINGO software generated worse solutions than the proposed algorithm, in which case 16 could outperform the others at 0.43% by PSO and 0.28% by DE. From case 17 to case 20, the LINGO software could not find a solution to the problem, while the proposed algorithm using PSO and DE was able to generate a solution easily in a relatively short period of time. With regard to the *RI* in a comparison of PSO and DE, Table 6.10 and Figure 6.12 (b) showed that the proposed algorithm using PSO produced outstanding results when compared to the DE. There were just two cases of the RI for which the average displayed a lower level of performance than DE (Cases 6 and 11). A summation of each problem group produces a positive value, which means that in all of the problem groups, the PSO performed far better when compared to the DE.

The proposed algorithm also has produced an error in the optimal solution, but that error is admissible and can still confirm the acceptability of the proposed algorithm's performance. When the small-sized problems were tested, the LINGO software outperformed the proposed algorithm in terms of both solution and runtime. In the medium-sized problems, the LINGO software was also able to generate an optimal solution and obtain a better solution than the proposed algorithm, but the time of the LINGO software was higher than that of the proposed algorithm using the PSO and DE. When the large-sized problems were experimented upon, the LINGO software was able to find a better solution than the proposed algorithm, even if it could not find the optimal solution. The runtime of the LINGO software required a significant amount of time. Although the trials in this study used 12 hrs to reach a solution, an optimal solution was not reached. When the very large-sized problems are analyzed, the LINGO software generated a less desirable solution than the proposed algorithm that employed metaheuristics. Furthermore, the runtime of the metaheuristics trials was faster than the runtime of the LINGO software. With regard to the employment of metaheuristics, though the DE utilized a shorter runtime than the PSO and outperformed the PSO in some cases in the medium- and large-sized problems, the PSO generally yielded outstanding results when compared to the DE because the overall results of the PSO could generate the final solution better than the DE, especially in the instances of "with limit location" that are shown in Figure 6.12.



(a) (b)

Figure 6.11 The total cost comparison of each solution between LINGO, PSO, and DE; (a) without the limit of location, (b) with the limit of location



(a) (b)

Figure 6.12 The *RI* of each solution between PSO and DE; (a) without the limit of location, (b) with the limit of location

6.5.3 Numerical tests for PWSCM improvement

In this section, we aim to represent the benefits of PWSCM improvement under integrated decisions for the on-site and off-site separation of recyclable materials. Although the superior performance of the mixed model has been confirmed in many studies and has been achieved in many real cases [17], we also desire to present the advantages of this model from a cost and economic perspective with respect to our proposed model. In this numerical test, Case 9 is used to show the performance of the proposed model, in which the post-disaster supply chain network consists of eighty affected zones, eighteen candidate TDWCSCs, twelve candidate TDWPRCs, nine candidate landfills, nine candidate markets and four RSR technologies. The proposed model is compared with the on-site separation model and off-site separation model in the handling of recyclable materials with respect to our system. The proposed model is reformulated for on-site separation and off-site separation. To formulate the on-site separation model, the proposed model in Section 3 is reformulated by adding equation 6.40. While the off-site separation model is formulated by adding equation 6.41. The numerical tests are solved without the limit of location. The solution results of the three models are tabulated in Table 6.11 and are shown in Figure 6.13.

$$\sum_{k} \xi b_{ik} = 0 \qquad \forall i \qquad (6.40)$$

$$\sum_{j} \xi a_{ij} = 0 \qquad \forall i \qquad (6.41)$$

From the solution results, we can see that the mixed separation model employed for handling recyclable materials could overcome the results of the on-site separation model and the off-site separation model. The highest total case in the off-site separation model was 18,589,503, while the total cost of the on-site and mixed separation models were 17,853,049 and 17,838,077, respectively. The mixed separation model could reduce the total costs at 4.04% from the total cost of the off-site separation model and 0.08% from the total cost of the on-site separation model. Based on the worst values of the fixed costs, transport costs, operational costs, revenue and penalty costs, the mixed separation model with respect to our proposed model was able to increase the level of performance with regard to costs in which all the worst values were obtained from off-site separation model. The superior performance based on the worst values is tabulated in the final column of Table 6.11. Based on a comparison between the on-site separation model and the mixed separation model, the mixed separation model was able to overcome the on-site separation model in terms of total costs, transport costs, and penalty costs at 0.08%, 0.16%, and 0.11%, respectively. Whereas, the on-site separation model could overcome the mixed separation model in terms of fixed costs, operational costs, and revenue yields at 1.50%, 0.04%, and 0.03%, respectively. Although some costs in the on-site separation model were preferred over the mixed separation model, the mixed separation model was still considered to be superior to the on-site separation model in terms of the overall costs.

Figure 6.13 reveals that the mixed separation model could not overcome all costs in both the on-site and off-site separation models simultaneously, but the mixed separation model could balance the costs of both models. Some costs were higher, but some costs were lower. Finally, the mixed separation model was able to minimize the total costs, as it was able to overcome both the on-site and off-site separation models. The mixed separation model could yield balanced results not only in terms of cost but also in terms of recycling rates, logistics, information management, resource availability and environmental and human effects [17]. As is stated in the above analysis, we have determined that our proposed model is capable of down system performance deficiencies in a post-disaster waste supply chain management context. This provided the empirical insight into how change is improved with regard to post-disaster waste supply chain management systems. With PWSCM improvement, this can be a benefit for the government in designing or planning the PWSCM strategy.

Table 6.11 The results of on-site, off-site, and mixed model separation for recyclable material in terms of cost (cost unit: $)

	On-site	Off-site	Mixed Model	% of changing	
Total cost (*Z*)	17,853,049	18,589,503	17,838,077	4.04%	(-)
Fixed cost (*FC*)	333,500	368,500	338,500	8.14%	(-)
Transport cost (*TC*)	11,599,307	12,113,922	11,580,392	4.40%	(-)
Operation cost (*OC*)	4,466,163	4,514,490	4,468,004	1.03%	(-)
Revenue (*R*)	1,759,015	1,733,091	1,758,498	1.47%	(+)
Penalty cost (*PC*)	3,213,094	3,325,682	3,209,679	3.49%	(-)

Note: The percentage of change is based on the worst value of the three models; the more negative value of *Z*, *FC*, *TC*, *OC* and *PC* is the superior performance of the worst value; the more positive value of *R* is the superior performance of worst value

Figure 6.13 The graphical model for cost comparison of on-site, off-site and mixed separation model

6.6. Conclusion

This research studied the problem of post-disaster waste supply chain management with respect to a minimization of total costs in the supply chain. The facility location and allocation problems were applied in this study. The objective function was to minimize the financial totals of the fixed costs and the variable costs, the penalty costs associated with the negative environmental and human effects, and the maximize potential revenue incurred from the sellable waste. The network structure of the proposed mixed-integer linear programming model was composed of the debris collection and separation sites, the processing and recycling sites, the disposal sites and the market sites with decision-making for locating the suitable temporary debris collection sites, processing sites and landfills and was used to facilitate the debris flow decision-making process. Furthermore, this model determined the separation of recyclable materials where debris is separated on-site or off-site and also determined the RSR technologies in this study as well. Since the problem is NP-hard, this chapter proposes employing two metaheuristic approaches with the encoding and decoding schemes to solve this problem. The performance values of the proposed algorithm by PSO and DE were evaluated using the set of generated cases and were compared with the results obtained from the exact solution method using LINGO software solver.

The experimental results showed that the proposed algorithm produced an error in the optimal solution or the best solution that was found within the computational time limit by LINGO software solver, but that error is considered admissible in terms of the acceptability of the proposed algorithm’s performance. In the small-sized problem, the LINGO software solver could overcome the proposed algorithm both in terms of runtime and solution. In the medium- and large-sized problems, the LINGO software solver could also find a better solution than the PSO and DE, but the runtime was longer than with the PSO and DE. While the very large-sized problem was tested, the proposed algorithm using the PSO and DE generally yielded outstanding results when compared to the LINGO software solver. This was true not only with regard to the final solution but also in terms of runtime when searching for a solution. To compare and analyze the performance of the two metaheuristic approaches, the results demonstrate that the PSO could be used as an efficient alternative approach for solving the post-disaster debris supply chain management problem since it was able to find an effective quality solution even if the runtime was longer than the DE. Finally, we have also proposed the numerical tests in order to determine the performance of the proposed model.

A key advantage of this research was to analyze the entire supply chain with regard to the post-disaster debris problem and to balance the advantages of the on-site and off-site separation processes of recyclable materials such as in terms of recycling rates, recycling costs, revenues, logistics, information management, resource availability and environmental and human effects. Moreover, the proposed model could be employed to serve emergency management purposes. Firstly, it could aid in the preparation stage including the spatial distribution of waste collection and the separation sites, the processing and recycling sites and the disposal sites, the assignment of waste in each affected community, and the relevant expectations in terms of budget-planning. The second is to aid in the recovery stage in order to provide debris flow and directions at each step of the post-disaster waste supply chain management process. Also, our proposed algorithms can be applied in the actual practice in decision-making in the operation for the purposes of facility location and distribution in the PWSCM problem. This can evaluate in a variety of scenarios with a variety of possible data in order to reach an acceptable solution by using the short computation time to reach a desired solution for the model. Due to the fact that substantial disasters will likely occur in the future as either natural disasters or man-made disasters, it is believed that the proposed algorithm can be employed to address this challenge. Our proposed algorithm can easily address the extensive issues associated with these disasters within a short computational amount of time. Furthermore, the proposed algorithm can be applied in the general waste management process as well. Further studies are recommended that should include other constraints in order to make addressing the problem more practical such as with regard to road closures or traffic congestion, different modes of transportation, different operation times or time schedules, the uncertainty of disasters, and in other such examples. The researchers have continued to investigate ways to improve the algorithm performance with a wider range of post-disaster debris management problems.

6.7 References

[1] World Health Organization. 2007., Risk reduction and emergency preparedness: WHO six-year strategy for the health sector and community capacity development. Available from: http://www.who.int/hac/techguidance/preparedness/emergency_ preparedness_ eng.pdf. Accessed 11 November 2015.

[2] Boonmee, C., Arimura, M., & Asada, T. (2017). Facility Location Optimization Model for Emergency Humanitarian Logistics. International Journal of Disaster Risk Reduction, 24, 485-498.

[3] Guha-Sapir, D., P. Hoyois, and R. Below. 2015., Annual Disaster Statistical Review 2014, The Numbers and Trends. Brussels, CRED.

[4] Akgün, İ., F. Gümüşbuğa, and B. Tansel. 2015., Risk based facility location by using fault tree analysis in disaster management. Omega 52, 168–179.

[5] Coppola, D. P. 2011., Introduction to international disaster management. Butterworth-Heinemann.

[6] G. Fetter, T. Rakes, Incorporating recycling into post-disaster debris disposal, Socio-Economic Planning Sciences, 46 (1) (2012) 14–22.

[7] Á. Lorca, M. Çelik, Ö. Ergun, P. Keskinocak, A decision-support tool for post-disaster debris operations, Procedia Eng. 107 (2015) 154–167.

[8] M. Lehtveer, F. Hedenus, Nuclear power as a climate mitigation strategy–technology and proliferation risk, Journal of Risk Research, 18 (3) (2015) 273–290.

[9] Public assistance damage assessment guidelines. Washington, DC: FEMA; 2008.

[10] N. Altay, W.G. Green, OR/MS research in disaster operations management, European Journal of Operational Research, 175 (1) (2006) 475–493.

[11] G. Galindo, R. Batta, Review of recent developments in OR/MS research in disaster operations management, Eur. J. Oper. Res. 230 (2) (2013) 201–211.

[12] A.M. Caunhye, X. Nie, S. Pokharel, Optimization models in emergency logistics: a literature review, Socio-Econ. Plan. Sci. 46 (1) (2012) 4–13.

[13] M.S. Habib, Y.H. Lee, M.S. Memon, Mathematical models in humanitarian supply chain management: a systematic literature review, Math. Prob. Eng. (2016).

[14] Lin Moe, T. (2010). Cleanup after Katrina: an analysis on policy, process, priorities, problems, and politics. Disaster Prevention and Management: An International Journal, 19(3), 314-332.

[15] Brandon, D. L., Medina, V. F., & Morrow, A. B. (2011). A case history Study of the recycling efforts from the United States army corps of engineers hurricane katrina debris removal mission in Mississippi. Advances in Civil Engineering, 2011.
[16] Karunasena, G., Amaratunga, D., Haigh, R., & Lill, I. (2009). Post disaster waste management strategies in developing countries: case of Sri Lanka. International Journal of Strategic Property Management, 13(2), 171-190.
[17] Brown, C., & Milke, M. (2016). Recycling disaster waste: Feasibility, method and effectiveness. Resources, Conservation and Recycling, 106, 21-32.
[18] FEMA (2007) 'Public assistance debris management guide'. Federal Emergency Management Agency. Available online at http://www.fema.gov/pdf/government/grant/pa/demagde.pdf, last accessed February 2016.
[19] USEPA, 2008. Planning for Natural Disaster Debris. Office of Solid Waste andEmergency Response, Office of Solid Waste, USEPA, Washington.
[20] UNEP (2012) 'Managing post-disaster debris: The Japan experience'. United Nations Environment Program.
[21] EPA (2008) 'Planning for natural disaster debris'. Environmental Disaster Agency. Available online at http://www.epa.gov/waste/conserve/imr/cdm/pubs/pndd.pdf, last accessed February 2016.
[22] Brown, C., Milke, M., & Seville, E. (2011). Disaster waste management: A review article. Waste management, 31(6), 1085-1098.
[23] Reinhart, D.R. and P.T. McCreanor (1999) 'Disaster debris management – Planning tools'. Report submitted to the United States Environmental Protection Agency.
[24] McEntire, D. A. (2006). Managing debris successfully after disasters: Considerations and recommendations for emergency managers. Journal of Emergency Management, 4(4), 23-28.
[25] Ekici, S., McEntire, D. A., & Afedzie, R. (2009). Transforming debris management: considering new essentials. Disaster Prevention and Management: An International Journal, 18(5), 511-522.
[26] Hu, Z. H., & Sheu, J. B. (2013). Post-disaster debris reverse logistics management under psychological cost minimization. Transportation Research Part B: Methodological, 55, 118-141.
[27] Pramudita, A., Taniguchi, E., & Qureshi, A. G. (2014). Location and routing problems of debris collection operation after disasters with realistic case study. Procedia-Social and Behavioral Sciences, 125, 445-458.
[28] Kim, J., Deshmukh, A., & Hastak, M. (2014). Selecting a Temporary Debris Management Site for Effective Debris Removal.
[29] Onan, K., Ülengin, F., & Sennaroğlu, B. (2015). An evolutionary multi-objective optimization approach to disaster waste management: A case study of Istanbul, Turkey. Expert Systems with Applications, 42(22), 8850-8857.
[30] Habib, M. S., & Sarkar, B. (2017). An Integrated Location-Allocation Model for Temporary Disaster Debris Management under an Uncertain Environment. Sustainability, 9(5), 716.
[31] New Zealand Department of Labour, 2011. Best Practice Guidelines for Demolitionin New Zealand. New Zealand Demolition and Asbestos Association.
[32] Kennedy, J., & Eberhart, R.C. (1995). Particle swarm optimization. In Proceedings of the IEEE International Conference on Neural Networks IV, 1000, 1942-1948.

[33] Wisittipanich, W., & Hengmeechai, P. (2017). Truck Scheduling in Multi-Door Cross Docking Terminal by Modified Particle Swarm Optimization. Computers & Industrial Engineering.

[34] Storn, R., & Price, K. (1995). Differential evolution–a simple and efficient adaptive scheme for global optimization over continuous spaces: technical report TR-95-012. International Computer Science, Berkeley, California.

[35] Wisittipanich, W., & Meesuk, P. (2015). Differential Evolution Algorithm for Storage Location Assignment Problem. In Industrial Engineering, Management Science and Applications 2015 (pp. 259-266). Springer, Berlin, Heidelberg.

[36] Wisittipanich, W., & Kasemset, C. Metaheuristics for Warehouse Storage Location Assignment Problems. CMUJ NS Special Issue on Logistics and Supply Chain Systems, 14(4), 361-377.

Chapter 7

Conclusions and Recommendations

7.1 Conclusions

This thesis aims to augment the efficiency disaster management and humanitarian logistics in facility location problem though optimization approach. A comprehensive analysis of disaster management and humanitarian logistics in facility location problem involves a review in chapter 2. In chapter 2, the optimization models for emergency humanitarian logistics' facility location problems were reviewed and analyzed for finding the problems and research gaps in this study. Four main models were investigated: deterministic, stochastic, dynamic, and robust. The deterministic facility location problem addressed facility location problems for minisum problems, covering problems, minimax problems, and obnoxious problems. This review attempted to survey the objectives, conditions, case studies, applications, disaster types, facility location types, solution methods, and emergency humanitarian logistics' facility location problem categories. The literature's main objective was found to be focused on responsiveness, risk, and cost-efficiency. In emergency humanitarian logistics problems, responsiveness and risk are the major criteria, with most models aiming to minimize response time, evacuation time and/or distance, transportation costs (distance and time), the number of open facilities, facility fixed costs or operating costs, uncovered demand, unsatisfied demand, and risk, along with maximizing the demand points covered. Depending on the problem type, the literature showed that the problem types could be merged with other problems and that the facility location problem could be applied along with other techniques such as decision theory, queuing theory, and fuzzy methods. Owing to the prevalence of earthquakes, hurricanes, floods, and epidemics in the world, these were the main focus of emergency humanitarian logistics research. An exact solution was found to be one efficiency technique, but advanced algorithms were found to be most effective for large-scale problems.

Since the problems and research gaps were found, this thesis was segregated into four sections that represented in chapter 3 – chapter 6. Those chapters were presented the different problem in each facility location problem of disaster management and humanitarian logistics issues. The minor approach in this thesis is optimization approach in which it was used to apply in this thesis for addressing each problem. Moreover, some tools were integrated with optimization approach in this thesis. The summary of all contributions was explained as follows;

Chapter 3 proposed a conceptual model for shelter sites selection and evacuation planning by considering both qualitative measurement and quantitative measurement. The optimization technique and multiple criteria decision making are applied in this study. This conceptual model was tested with a real case study in Banta Municipality, Thailand. Firstly, an optimization technique was proposed to create plans for shelter site selection and evacuation planning. The mathematical models were formulated under different conditions and model types for considering the assignment of a community to a nearby shelter, the capacity of shelter, the distance limit, the number of shelter sites, and the number of demand. In this study, four mathematical models were formulated. After proposed mathematical models were coded and run in optimizer tool, the result of four models was evaluated by local government (Decision makers) in which Analytic Hierarchy Process (AHP) technique with the fuzzy approach was applied to analyze all models. The alternative models were inspected with respect to five main criteria namely; accessibility, availability, sustainability, and risk. Moreover, it also is inspected with respect to eight sub-criteria that compose of evacuation, medical care services, material reverse warehouse, shelter, long-term planning and flexibility, a total distance of evacuation, distance from the source of danger, geological hazard, and topographic risk. As the result, we found that the Model III outperforms the other models. This chapter will be great significance in helping decision makers consider placement of emergency shelter and evacuation planning with respect to qualitative measurement, quantitative measurement and the uncertainty and vagueness of expert's opinion. In addition, by standing our methodology clearly and numerically, our conceptual model can be a guide of the methodology to be implemented to other problems as well. To recommend for others application, the mathematical model does not need to formulate same as this study. The researchers can design following research's opinion and used several objective functions or several constraints since it might show more efficient solution than this research. Moreover, although the Fuzzy AHP is useful for this study, it still consists some limitations and some problem such as subjective nature of decision makers, the complexity of analysis (too many criteria), and difficulty of quantifying importance for some criteria.

Chapter 4 presented a stochastic linear mixed-integer programming mathematical model for flood evacuation planning to optimize decision related to shelter site selection under hierarchical evacuation planning. The proposed mathematical model considers minimum expected population-weighted travel distance as the objective function. This study not only provides a flood shelter but also determines hierarchical evacuation concept, distribution of shelter, utilization of shelter, capacity restrictions of shelter and evacuee's behavior for flood disaster that balances the preparedness and risk despite the uncertainties of flood events. The proposed model was validated by generating a base case scenario using real data for Chiang Mai province, Thailand. Besides, we also proposed sensitivity analysis for more guideline under uncertainty decision. This study will be great significance in helping policymakers consider both spatial and performant aspect of the strategic placement of flood shelters and evacuation planning under uncertainties of flood scenario. The implementation of the proposed mathematical model also has limitations. According to unlike another natural disaster, it cannot be generated to others disaster due to some condition of each natural disaster are different such as shelter type, time condition, etc. However, our mathematical model can apply to any other city in flood situation as well.

Chapter 5 proposed a stochastic linear mixed-integer programming mathematical model for developing flood evacuation planning and shelter site selection under hierarchical evacuation planning and probabilistic scenario. The proposed mathematical model considers two criteria as an objective function: minimum expected total travel distance and minimum expected total risk index of shelter. The proposed model not only provides a flood shelter and population assignment but also scrutinizes hierarchical evacuation concept, evacuee's behavior and uncertainty of events. Our proposed model was validated with probabilistic scenarios due to the uncertainty that surrounds disasters and their consequence. A flood hazard map of Chiang Mai province in Thailand was used to generate disaster scenarios with different probabilities of events that closely match a real flood problem. To provide a guideline for decision makers, we proposed epsilon constraint approach to solve the proposed mathematical model in which it can handle multiple and conflicting criteria problem. This chapter presented several solutions for decision makers on selecting an efficient solution that showed expected total travel distance, expected total risk index of shelter, selected shelters and planning budget. Furthermore, this chapter presented the solution point in term of the trade-off between the value of expected total travel distance and value of expected total risk index of shelter. This proposed model will be great significance in helping decision makers consider spatial, financial, and risk aspects of the strategic placement of flood shelters and flood evacuation planning under uncertainty of flood scenarios that balance two criteria; travel distance and risk index of shelter.

Chapter 6 studied the problem of post-disaster waste supply chain management with respect to a minimization of total costs in the supply chain. The facility location and allocation problems were applied in this study. The objective function was to minimize the financial totals of the fixed costs and the variable costs, the penalty costs associated with the negative environmental and human effects, and the maximum potential revenue incurred from the sellable waste. The network structure of the proposed mixed-integer linear programming model was composed of the debris collection and separation sites, the processing and recycling sites, the disposal sites and the market sites with decision-making for locating the suitable temporary debris collection sites, processing sites and landfills and was used to facilitate the debris flow decision-making process. Furthermore, this model determined the separation of recyclable materials where debris is separated on-site or off-site and also determined the RSR technologies in this study as well. Since the problem is NP-hard, this chapter proposes employing two metaheuristic approaches with the encoding and decoding schemes to solve this problem. The performance values of the proposed algorithm by PSO and DE were evaluated using the set of generated cases and were compared with the results obtained from the exact solution method using LINGO software solver. The experimental results showed that the proposed algorithm produced an error in the optimal solution or the best solution that was found within the computational time limit by LINGO software solver, but that error is considered admissible in terms of the acceptability of the proposed algorithm's performance. In the small-sized problem, the LINGO software solver could overcome the proposed algorithm both in terms of runtime and solution. In the medium- and large-sized problems, the LINGO software solver could also find a better solution than the PSO and DE, but the runtime was longer than with the PSO and DE. While the very large-sized problem was tested, the proposed algorithm using the PSO and DE generally yielded outstanding results when compared to the LINGO software solver. This was true not only with regard to the final solution but also in terms of runtime when searching for a solution. To compare and analyze the performance of the two metaheuristic approaches, the results demonstrate that the PSO could be used as an efficient alternative approach for solving the post-disaster debris supply chain management problem since it was able to find an effective quality solution even if the runtime was longer than the DE. Finally, we have also proposed the numerical tests in order to determine the performance of the proposed model. A key advantage of this research was to analyze the entire supply chain with regard to the post-disaster debris problem and to balance the advantages of the on-site and off-site separation processes of recyclable materials such as in terms of recycling rates, recycling costs, revenues, logistics, information management, resource availability and environmental and human effects. Also, our proposed algorithms can be applied in the actual practice in decision-making in the operation for the purposes of facility location and distribution in the PWSCM problem. Our proposed algorithm can easily address the extensive issues associated with these disasters within a short computational amount of time.

All contributions represented how to improve or develop the disaster management and humanitarian relief logistics in facility location problem in which all contributions have presented benefits for supporting the efficient operations in this issue with regard to mitigation phase, preparedness phase, response phase, and recovery phase. The main advantage of this thesis will be a great significance not only in helping policymakers or governors consider the spatial aspect of the strategic placement of each facility location problem but also in helping victims during the emergency circumstances as well.

7.2 Recommendations

This thesis expects that the recommendations to be presented in this section will be beneficial for future research especially in the fields relating to disaster management and humanitarian logistics. Due to the research is segregated into four sections, hence the recommendation will be proposed following each chapter. The recommendations of this thesis are as follows.

Chapter 3: To recommend for others application, the mathematical model does not need to formulate same as this study. The researchers can design following research's opinion and used several objective functions or several constraints since it might show more efficient solution than this research. Moreover, although the Fuzzy AHP is useful for this study, it still consists some limitations and some problem such as subjective nature of decision makers, the complexity of analysis (too many criteria), and difficulty of quantifying importance for some criteria.

Chapter 4: Although this proposed conceptual model is quite complicated, it can respond to many criteria completely. Consequently, the policymaker should decide carefully to apply in a real case. To reduce a complexity, the affected communities should not be separated too many because it will be difficult for evacuation management. In future research, the proposed model should consider in road closures or traffic congestion, road network, a difference of travel speed depending on the mode selection and accessibility of shelter site that may affect to an efficient evacuation. Furthermore, this model should consider financial cost and risk of open shelter at potential flooding area as well.

Chapter 5: In future research, the model should consider in road closures or traffic congestion, utilization of shelter and the weight associated with each demand point that may affect an efficient evacuation. Moreover, this model should concentrate on construction cost as objective function simultaneously because it will be an advantage for the local government.

Chapter 6: Further studies are recommended that should include other constraints in order to make addressing the problem more practical such as with regard to road closures or traffic congestion, different modes of transportation, different operation times or time schedules, the uncertainty of disasters, and in other such examples. The researchers have continued to investigate ways to improve the algorithm performance with a wider range of post-disaster debris management problems.

Appendix A
Journals, Proceedings and Conferences, Awards and Society member

Journals

[1] Boonmee, C., Takumi, A., & Mikiharu, A. (2018) Location and Allocation Optimization for Integrated Decisions on Post-Disaster Waste Supply Chain Management: On-site and Off-site Separation for Recyclable Materials. International Journal of Disaster Risk Reduction (In press).

[2] Boonmee, C., Takumi, A., & Mikiharu, A. (2018) A Bi-Criteria Optimization for Hierarchical Evacuation and Shelter Site Selection under Uncertainty of Flood Events. Journal of the Eastern Asia Society for Transportation Studies, 12(2017), p. 251-268.

[3] Boonmee, C., Takumi, A., & Mikiharu, A. (2017) Improving Evacuation Planning and Shelter Site Selection for Flood Disaster: Thai Flooding Case Study. Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management), Vol. 73(5), p. 253-267.

[4] Boonmee, C., Naotaka, I., Takumi, A., & Mikiharu, A. (2017) An Integrated Multi-Model Optimization and Fuzzy AHP for Shelter Site Selection and Evacuation Planning. Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management), Vol. 73(5), p. 225-240.

[5] Boonmee, C., Mikiharu, A. & Takumi, A. (2017) Facility Location Optimization Model for Emergency Humanitarian Logistics, International Journal of Disaster Risk Reduction, Vol. 24, p. 485-498.

[6] Naotaka, I., Takumi, A., Boonmee, C., & Mikiharu, A. (2016). Built on The Local Disaster Prevention Education tool using Evacuation Drill Probe Data. Journal of Japan Society of Civil Engineers, Vol. 72(5), p. 331-339. (Japanese)

[7] Kasemset, C. & Boonmee, C. (2015). Different Cost Allocation Methods in Material Flow Cost Accounting: A Case Study of Waste Reduction in Thai Meatball Production. Chiang Mai University Journal of Natural Sciences Special Issue on Logistics and Supply Chain Systems, Vol. 18(4), p. 379-388

[8] Boonmee, C & Kasemset, C. (2014). Optimization of Distribution Network with Backhaul, International Federation of Logistics and SCM Systems, Vol. 8(1), p. 21-28.

[9] Boonmee, C & Kasemset, C. (2014). The Application of Distribution Network Optimization: Case Study of Canned Fruit Industry, Thai Journal Operation Research, Vol. 2(2), p. 1-10. (Thai)

[10] Kasemset, C, Sriphen, C & Boonmee, C (2014). Application of Material Flow Cost Accounting Analysis Technique for Reworks Reduction. UBU Engineering Journal. 1(7). (Thai)

Proceedings and Conferences

[1] Kasemset, C. & Boonmee, C. (2016). An Integration Method of MFCA, Dynamic Programming, and Multiple Criteria Decision Making in Operations Improvement: A Case Study. Proceeding of the 2017 International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, December 10 - 13, p. 1844-1853.

[2] Boonmee, C., Takumi, A., & Mikiharu, A. (2017) The Multi-Objective Fuzzy Mathematical Programming for Facility Location Problem in Humanitarian Relief Logistics, In Proceedings of Joint Symposium on Mechanical - Industrial Engineering, and Robotics 2017, Chiang Mai University, Thailand, November 15 - 17, 2017.

[3] Kazuma, M., Naotaka, I., Takumi, A., Boonmee, C., & Mikiharu, A. (2017). Analysis of Relationship between Disaster Prevention Consciousness and Evacuation Required Time in Muroran city, In Proceedings of Joint Seminar on Environmental Science and Disaster Mitigation Research 2017 (JSED2017), March 2, 2017, pp. 93-94.

[4] Boonmee, C., Takumi, A., & Mikiharu, A. (2016) Improving evacuation planning and shelter site selection for flood disaster: A stochastic approach, In Proceedings of infrastructure planning in Japan Society of Civil Engineers, Vol. 54, p. 2313-2321.

[5] Boonmee, C., Naotaka, I., Takumi, A., & Mikiharu, A. (2016) Multi-model optimization for shelter-site selection: A case study in Banta municipality, Thailand, In Proceedings of infrastructure planning in Japan Society of Civil Engineers, Vol. 53, p. 2175-2181.

[6] Kasemset, C., Boonmee, C., & Khuntaporn P. (2016). Application of MFCA and ECRS in Waste Reduction: A Case Study of Electronic Parts Factory, Proceeding of the 2016 International Conference on Industrial Engineering and Operations Management, Malaysia, March 8-10, p. 1844-1853.

[7] Naotaka, I., Takumi, A., Boonmee, C., & Mikiharu, A. (2015). Built on The Local Disaster Prevention Education tool using Evacuation Drill Probe Data. In Proceedings of infrastructure planning in Japan Society of Civil Engineers, Vol. 52, (Japanese)

[8] Boonmee, C & Kasemset, C. (2015). A Conceptual Model for combining MFCA and Dynamic Programming. Joint Symposium on Mechanical-Industrial Engineering and Robotics 2015, Muroran Institute Technology, Japan, May 29 - 30, 2015.

[9] Chaiwan, W. Boonmee, C & Kasemset, C. (2015). Application of Material Flow Cost Accounting Analysis Technique in Meat Ball Production. International Congress on Logistics and SCM Systems 2015 Conference, Thailand, July 1 - 4 2015, pp 183-193,

[10] Boonmee, C & Kasemset, C. (2015). Simulation of Distribution Network Optimization: Case Study of Canned Fruit Industry. OR-Net Conference 2015, Kasetsart University, Thailand, March 26 - 27 2015. (Thai)

[11] Boonmee, C & Kasemset, C. (2014). Distribution Network Optimization Considering Backhaul in Supply Chain Management. OR-Net Conference 2014, Naresuan University, Thailand, September 6 - 8 2014. (Thai)

[12] Boonmee, C & Kasemset, C. (2013). Operations Improvement in Goods Transportation: A Case study. Joint Symposium on Mechanical-Industrial Engineering and Robotics 2013, Chiang Mai University, Thailand, November 14 - 17, 2013.

[13] Boonmee, C & Kasemset, C. (2013). Productivity Improvement in Goods Transportation via Bus Container Case study: Chaipattana Transportation Chiang Mai Co., Ltd. The 20th Tri-University International Joint Seminar & Symposium 2013, Mie University, Japan, October 28 – November 1, 2013.

Awards

[1] Outstanding presentation award of the 12th EASTS international conference held on 18-21 September 2017 in Ho Chi Minh City, Vietnam. (2017).

Society members

[1] Japan Society of Civil Engineer (JSCE)
[2] Eastern Asia Society for Transportation Studies (EASTS)