Doctoral Dissertation

A Study on Facility Location-allocation Models for Humanitarian Relief Logistics

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Abstract

Decision-making on shelter location-allocation is the most critical part of humanitarian relief logistics because it affects security of victims and influences the success of disaster management strategy. Without an appropriate approach for determining shelter location-allocation, decision-makers would make ad-hoc decisions which result in high cost, slow response, and failure to rescue the victims.

Proposing facility location-allocation models in the context of humanitarian logistics, monetary criterion cannot be ignored because it helps decision-makers to sufficiently prepare the grant aid for disaster relief purposes. In the same way, considering monetary and non-monetary criteria simultaneously helps to ensure that the victims are being taken care well under the optimal relief budget. Furthermore, the proposed models should be solved by proper approaches to generate optimal solutions. The victims and decision-makers would get the benefit if the proposed models could simplify prompt decision-making for determining location-allocation in response to disasters.

This study aims to propose the optimization models to determine shelter location-allocation in response to disaster. In addition to the models, a novel approach for dealing with large scale location-allocation is proposed. Therein, four models are formulated to consider proper locations to use as shelters. The first model seeks to determine shelter location-allocation with total cost minimization. The proposed mathematical model is solved by Genetic Algorithm. The second model considers both monetary and non-monetary for justifying shelter location-allocation. The objectives of the model are to simultaneously minimize total cost, total evacuation time, and number of open shelters. The proposed mathematical model is solved by Epsilon Constraint method and Goal Programming which are the posteriori and priori methods respectively. The third model seeks to concurrently minimize total cost, and total evacuation time. The proposed model is solved by a novel approach that integrated Epsilon Constraint method and Artificial Neural Network to facilitate fast decision-making. To the best of our knowledge, there are no existing works that combined these methods in coping with location-allocation problems, especially in field of humanitarian relief logistics. The fourth model involves multi-echelon relief facilities location-allocation. The first echelon determines appropriate shelter location-allocation to minimize total cost and minimize total evacuation time, while the second echelon involves justifying distribution center location-allocation to minimize distribution cost. The proposed model is solved by Epsilon Constraint method.

The applicability of the proposed models and proposed solution approach is validated through the case study of shelter location-allocation in response to flooding in Surat Thani, Thailand. The results generated by each model are compared with the current shelter location-allocation plan determined by the government sector. The comparison results indicate that considering appropriate shelter location-allocation based on proposed models mostly produces lower total cost than the current plan. It is plausible to use the proposed models and proposed solution approach to improve disaster response for the benefit of victims and decision-makers.

Keywords: Disaster Management, Epsilon Constraint Method, Genetic Algorithm, Goal Programming, Artificial Neural Network

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Natural disasters have caused enormous damage to humankind, animals, social and economic sectors. In 2019, the occurrences of catastrophes were more frequent than in any year in the previous decade. Based on statistical data reported by the Centre for Research on the Epidemiology of Disasters (CRED), there were 396 natural disaster events, 11,755 deaths, 95 million affected people, and resulted in $103 billion economic losses. Among all disasters, flooding took the most drastic effects on people which causing death. The statistical report also revealed that Asian was the continent that most affected by catastrophes [11].

According to the uncertainty of catastrophe events, disaster management plays an important role in dealing with the hazard phenomena caused by both natural and man-made. Disaster management is a systematic approach for alleviating victims' suffers through the processes of mitigation, preparedness, response, and recovery [40, 46]. Humanitarian logistics involves in facilitating disaster management processes as well as enhancing the effectiveness, efficiency, and equity of the relief logistics and supply chain.

Unlike traditional or commercial logistics which seeks profitability, humanitarian logistics aims at decreasing losses and healing the sufferers. The activities of humanitarian logistics are more complex because the resources and budgets for relief purposes would not be increased although the impacts of disasters are expanding. The mentioned activities include evacuating the victims from the affected areas to safe places, planning, storing, and distributing relief supplies such as temporary shelters, foods, potable water, survival bags, medical supplies, tents, generators, etc. [58, 59] to alleviate the victims' suffering at the right time, right quantity to the right place [34, 54]. The decision-makers must conduct the relief activities carefully because there are several constraints that should be considered such as response time, availability of relief facilities, relief supplies, etc. Furthermore, decision-makers must ensure that all activities can rescue the victims equally [57].

Humanitarian logistics also involves selecting the appropriate locations of relief facilities such as temporary shelters, medical centers, healthcare centers, warehouses, or distribution centers [47, 48]. In this case, determining proper locations to establish these relief facilities is very important due to it involves several parties in relief supply chain. Moreover, it requires a great deal of money for investment and takes long-term effects on the stakeholders. In addition to all relief facilities, decision making on shelter location-allocation is the most critical part in humanitarian relief logistics because it involves the victims' securement [47]. However, the crucial criteria both in terms of monetary and non-monetary are required to consider when selecting the proper sites, otherwise, the related organizations would make ad-hoc decisions that lead to high cost, waste of resources, and slow response, and unable to serve the victims [2].

1.2 Research motivation

Lacking an appropriate approach for determining shelter location-allocation, the decision-makers could make ad-hoc decisions which causing overwhelming costs, slow response, and failure in rescue the victims. Previously, many publications presented the optimization models for dealing with location-allocation problem. Majority of the research works usually consider either monetary criteria (e.g., minimizing total cost, operation cost, transportation cost, etc.) and non-monetary criteria (e.g., minimizing distance, time, or maximize demand coverage). Although humanitarian logistics does not aim at profitability, but cost criteria cannot be ignored.

For the publications that proposed multi-objective optimization models in which monetary and non-monetary criteria are considered simultaneously, the employed solution approaches rather involved weighted assigning i.e., Weighted Sum Method (WSM), Weighted Goal Programming (WGP). The weighted coefficients are assigned to both monetary and non-monetary objectives in order to express the significance of a particular objective function. However, in the context of humanitarian logistics which attempts to help sufferers, these criteria cannot be compared the importance via weighted assignment. The decision-makers cannot state whether monetary or non-monetary are more important. As a result, the decision-maker will be under pressure when determining location-allocation. Therefore, the aforementioned solutions are not suitable to deal with location-allocation in response to humanitarian logistics.

According to the literature review, relief facility location-allocation problems are typically conducted based on an optimization basis. Dealing with location-allocation by optimization method can generate optimal solutions, but intensive computational time is required, especially when several objectives are determined concurrently. Thus, integrating optimization techniques with other applications would be advantageous when dealing with location-allocation in response to disasters in which fast decision fast decision-making is necessary. To the best of our knowledge, there are no existing works integrating optimization basis with machine learning for determining facility location-allocation problems, especially in the area of humanitarian logistics. Thus, there still room for proposing a novel approach for determining proper facilities location-allocation.

1.3 Research goals

The research goals of this study involve proposing the models to facilitate decision-making of shelter location-allocation for the benefit of decision-makers and the victims. In addition to the models, this study aims to propose the novel approach to support fast decision-making of shelter location-allocation to response to disaster. To achieve the research goals, four models are developed and aligned by each goal as follows:

Goal 1: Proposing the models to facilitate decision-making of shelter location-allocation for the benefit of decision-makers and victims.

Model 1: Efficient shelter location-allocation model

The first model involves a single objective optimization for shelter site selection and allocation. This model aims at minimizing the total cost which determined based on cost of opening the shelters, victims' transportation cost, and service cost that paid during the stays of victims. The optimal solution generated by the proposed model is compared with the current shelter location-allocation plan which is justified by the government agency.

Model 2: Multi-objective optimization model for shelter location-allocation

The second model involves multi-objective optimization model for determining shelter location-allocation. There are three objective functions that include in the model i.e. minimizing total cost, minimizing evacuation time, and minimizing the number of open shelters. Then, the optimal solution generated by solving single objective and multi-objective optimization is compared. This study also raises the idea that selected shelters should be located far enough from the disruption points or the affected areas to ensure safety. Hence, the concept to determine the appropriate minimum distance between the affected areas and candidate shelters is presented.

Model 4: Two-stage facility location-allocation model in response to relief supply chain

The fourth model is the effort to extend the applicability of the prior model to multi-echelon facility location-allocation model. The first echelon involves disaster response phase which seeks the proper shelters to serve the affected area. The second echelon relates to disaster preparation phase which aims to select the appropriate distribution center to serve the selected shelters. This model is conducted to see the possibility of a future study that attempts to extend the proposed model and test with the large-scale case study data.

2. Proposing the novel approach for support fast decision-making of shelter location-allocation in response to disaster.

Model 3: A novel approach for determining shelter location-allocation in humanitarian relief logistics

The third model is extended from the second model. The additional positive coefficient is augmented to the effective criteria i.e. victim's evacuation time in order to avoid obtaining inefficient solutions that occasionally occur when employing Epsilon Constraint method to solve multi-objective optimization model. Herein, the augmented positive coefficient is examined regarding the allowance time caused by personal allowance, delay, and fatigue which occur during victim's evacuation process. The results obtained by solving the multi-objective optimization problem are then prepared and simulated in several patterns. In this matter, the Artificial Neural Network (ANN) is employed to construct the mechanism for predicting the large-scale shelter location-allocation in the future.

1.4 Originality of research

The originality of this dissertation mainly relates the model formulations that considering the important criteria i.e. monetary, and simultaneously considering both monetary and non-monetary criteria. The powerful solution approach Epsilon Constraint is employed for dealing with the multi-objective optimization problems to avoid assigning weighted coefficient to the incomparable objective functions in which the prior works did not take into account this matter. Moreover, machine learning i.e. ANN is integrated with an optimization method for coping with location problems. To the best of our knowledge, there are no existing works integrated the Epsilon Constraint method with ANN to address shelter location-allocation problem in response to humanitarian logistics.

1.5 Organization of dissertation

The structure of dissertation is divided into seven chapters as described below:

- Chapter 1 describes the research background, research motivation to express the significance of the research, research aims, and the originality of this research.

- Chapter 2 presents the survey of literature relates to facility location-allocation problems in the areas of humanitarian logistics. The literature review is divided regarding the disaster phase, and summarize in terms of model formulation, solution methods, and application of the proposed model.

- Chapter 3 presents the efficient shelter location-allocation model. This chapter encompasses the research motivation, a model formulation which encompasses preliminary parameter estimation, indices, parameters, decision variable, objective function, and a set of constraints. The applicability of the proposed model is demonstrated through the case study of shelter site selection during a great flood in Tha Uthae, Surat Thani, Thailand. The optimal solution generated by the proposed model is compared with the current shelter allocation plan. Moreover, the sensitivity analysis is performed to see how the objective functions change when the maximum acceptable distance between the affected area and shelter is relaxed, which notice the decision-makers on how to set the appropriate policy on defining the proper maximum acceptable distance.

- Chapter 4 proposes the multi-objective optimization model in which the effectiveness and efficiency are included in formulating the model. The concept to determining the appropriate minimum acceptable distance between affected areas and candidate shelters is presented. The applicability of the proposed model is tested via the a case study of shelter location-allocation during the great flood in Tha Uthae, Surat Thani, Thailand. https://www.overleaf.com/project/60233acfa0ac403252dd4bb1

- Chapter 5 presents an integrated Artificial Neural Network (ANN) for decision making on shelter location-allocation. This model is extended from the model multi-objective optimization model in chapter 4. Only significant objective functions are included in the model. First, the multi-objective optimization model for shelter selection and allocation is solved by Epsilon constraint methods. Then, the obtained optimal solution is simulated and executed by Artificial Neural Networks in order to construct the mechanism for predicting the large-scale shelter location-allocation in the future.

- Chapter 6 proposes the two-stage relief facility location-allocation model for humanitarian supply chain. This model is developed to prove that the proposed method can solve several echelons in the humanitarian supply chain which could help as a guideline for future research.

- Chapter 7 express the concluding remarks, limitations, research contributions, and future works

Chapter 2

Literature Review

Humanitarian logistics plays the important role in terms of mobilizing the sufferers from the disrupted areas to secure zones and managing the flows of relief resources, knowledge, as well as skills in order to alleviate the trouble from the catastrophes attacking which caused by nature and human-made. In this case, considering the appropriate locations for establishing necessary facilities in coping with catastrophes and emergencies require thorough planning since a great deal of money is invested. Moreover, it's effects span a long time horizon impact and influence the success of disaster management [6, 18]. The decision making of facility location is not only concerned with selecting the most proper places but also includes allocating the facilities to the appropriate demand nodes [5]. The necessity of relief facility location-allocation regarding disaster phase, and research gap are summarized in next section.

2.1 Relief facility location-allocation based on disaster phase

The roles of relief facilities based on disaster stage can be classified as pre-disaster stage, and post-disaster stage (Figure 2.1). The facilities that are established to tackle the pre-disaster phase encompass permanent distribution centers, permanent shelters, warehouses, and safety areas. In post-disaster,

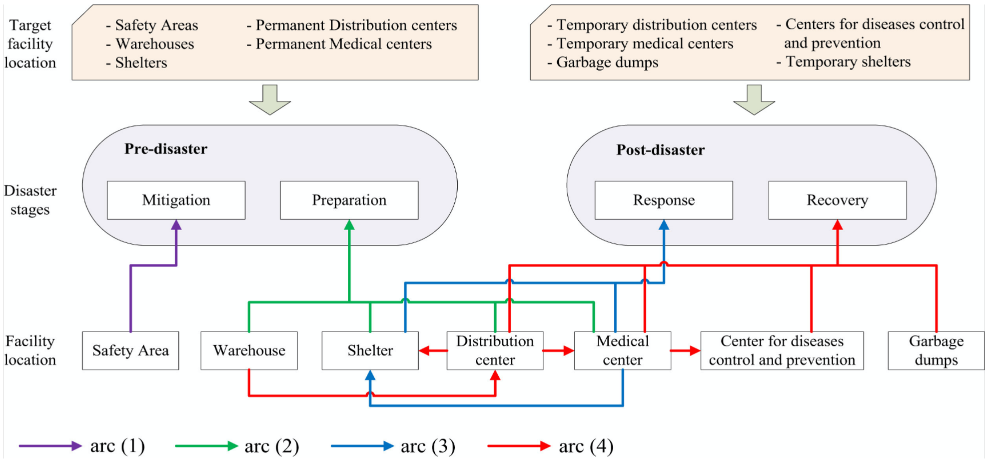


Figure 2.1: Facility types in each disaster stage
Boonmee et al. [6]

majority of the facilities are temporarily established for dealing with urgent situations such as temporary shelters, temporary distribution centers, temporary medical centers, disease control and prevention centers, and garbage dumps [6].

There are many academic works related to facility location-allocation problem for dealing with humanitarian logistics and disaster management. The researchers define and collect important data related to the characteristics of relief requirements and available resources to develop the mathematical models for determining location-allocation. The roles of facilities location-allocation regarding the disaster phases, model formulations, solution methods, and the applications can be concluded as follows:

2.1.1 Pre-disaster

The facilities that are established to tackle the pre-disaster phase encompass permanent shelters, permanent distribution centers, warehouses, and safety areas. Mete and Zabinsky [40] developed the two stages stochastic model to decide location-allocation of warehouse medical supplies during the disaster. The objective function in this stage sought to establish the warehouses with the minimum operating cost while the objective function in the second stage attempted to minimize total transportation time and the penalty of unfulfilled demand. The proposed model was tested with a case study of the earthquakes in Seattle and solved by the Exact Algorithm.

Mejia-Argueta et al. [39] proposed the multi-criteria optimization model for determining location-allocation of the emergency facilities. Several objective functions were set to improve the effective criteria included minimizing the maximum evacuation flow time, maximum supply flow time. Whereas efficient criterion was improved to minimize the total cost. The formulated model was verified based on the flood problem in Mexico. The Non-dominant solutions obtained through two techniques i.e. Weighted Sum Method and Epsilon Constraint.

Barzinpour and Esmaeili [3] formulated the multi-objective optimization model to maximize the population's coverage and minimize the logistics cost for determining emergency facilities location-allocation. The application of a proposed model was tested with the real-world problem i.e.urban districts in Iran, and solved by the Goal Programming approach.

Miç and Koyuncu [41] conducted the multi-objective model to identify the location-allocation of primary healthcare centers in the vulnerable area of Syria. The developed objective functions sought to minimize total cost for opening the facilities, minimize operation cost, minimize transportation cost, maximize demand coverage, maximize number of open facilities that installed laboratory, blood service, vaccination service, solar service, and internet service. The multi-objective optimization was solved by Weighted Goal Programming. The Analytic Hierarchy Process (AHP) was conducted to estimate the weight for assigning in Weighted Goal Programming. The model was solved by using the optimization package together with a geographic information system (GIS). Kanoun et al. [26] developed the single objective optimization model to justify the location-allocation of fire emergency stations. This study incorporated the satisfaction function to identify the decision-makers' preferences. The objective function of the proposed model was to maximize the decision-makers' satisfaction. The Goal Programming approach was employed to solve the proposed model. The application was illustrated via the case study of Sfax city in Tunisia.

Burkart et al. [9] proposed the multi-objective optimization model for decision making on distribution centers placement. The first objective aimed at minimizing total traveling cost and fixed cost for opening the distribution centers, while other objective attempted to minimize the unserved demand. The application of the developed model was tested with the real-world drought problem on Mozambique. The Pareto front generated the from the Epsilon Constraint method.

Horner and Downs [21] presented the warehouse location-allocation model that sought to minimize the transportation cost which occurred when distributed the relief goods to serve the victims who suffered the hurricane disaster in North Florida, USA. In this case, the model was solved by the GIS-based optimization package.

Ahmadi et al. [1] formulated a mixed integer nonlinear programming model to determine the location-routing of depots in-last mile transportation phase. In term of location-allocation, the model sought to minimize the traveling time, penalty cost of unmet demand, and fixed cost of opening depot. The proposed model was applied to the earthquake case study in San Francisco and solved by the Exact Algorithm.

Lauras et al. [31] developed a mixed integer stochastic programming model to cope with warehouse location-allocation problem. The proposed model also considered the probability that potential warehouse would be damaged by the disaster. Therein, the objective of the developed model sought to minimize unsatisfied transportation and logistics cost.

Ma et al. [33] presented the optimization model for determining the location-allocation of medical supply warehouses. The objective function intends to minimize the number of selected warehouses, cost of establishing warehouses, and traveling distance. In this study, Particle Swarm Optimization was implemented and demonstrated through the case study of the disaster that occurred in Beijing Tianjin Hebei, China.

2.1.2 Post-disaster

The relief facilities in the post-disaster stage are mostly temporarily established in responding to urgent situations such as temporary shelters, temporary distribution centers, temporary medical centers, disease control and prevention centers, and garbage dumps. The existing papers rather focused on developing the models to justify temporary shelter location-allocation.

Hallak et al. [20] proposed the multi-objective model to justify the proper locations for setting the shelters in Idleb, Syria. The objectives of the proposed model attempted to maximize the covered the victims and their demands for necessary relief supplies i.e. portable water, sensitization and hygiene facilities, while cost for operating still meant to be minimized. The Weighted Goal Programming was employed for addressing the multi-objective problem. The preference values obtained by interviewing the related stakeholders i.e. beneficiaries, experts, community representatives.

Kongsomsaksaku and Yang [28] presented the bi-level programming to justify the shelter location-allocation for flood evacuation planning in Utah, United States. The first level aimed at determining the number and the location of the shelters that generated the minimum total evacuation time. The second level was decided in the viewpoint of evacuees that sought the best routes to travel to the selected shelters under the shelters' capacity restriction. The Genetic Algorithm was handled to solve the proposed model.

Qin et al. [50] constructed the multi-objective model for evaluating shelter location-allocation during the earthquake in Beijing, China. The objective functions were designed to minimize evacuation distance, weighted evacuation distance, number of shelters, and the area for establishing the shelters. In order to deal with several objectives, the modified Particle Swarm Optimization Algorithm was used to solve the problem.

Görmez et al. [16] developed a multi-objective model for two stages of shelter location-allocation in preparation for the earthquake in Istanbul, Turkey. In the first stage, the objective function was set to minimize the demand weighted distance between the neighborhoods and the temporary shelters. The second stage presented the bi-objective model that meant to minimize the average evacuation distance to the new assigned facilities and minimize number of selected facilities for serving the refugees. Herein, the Epsilon Constraint method was employed to solve the bi-objective optimization.

Ozbay et al. [47] formulated the three echelons shelter site selection and allocation model under the uncertainty of the earthquake aftershock scenarios in Istanbul, Turkey. The objective function aimed at minimizing the number of selected shelters in each echelon. The proposed model was solved through Exact Algorithm.

Kilci et al. [27] developed the mixed integer linear programming for locating the temporary shelter for dealing with the aftermath of the earthquake. The model sought to select the best possible combination of shelters area and assign the threat zones to the closest open shelters under the shelters' capacity restriction. In this study, the proposed model was applied to the case study of the earthquake in Kartal, Istanbul, Turkey.

Boonmee et al. [8] formulated mathematical model for shelter site selection allocation to minimize the traveling distance between the affected areas and the selected shelters. The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) was performed to choose the most proper plan based on the expert's opinions. The numerical experiment was conducted through the case study of the flood in Chiang Mail, Thailand.

Horner et al. [22] presented a geographic information systems-based method for selecting the special needs shelters to satisfy the elderly casualties during hurricane attacking in the United States. The developed model attempted to minimize the transportation cost between the community and the selected shelter. In this regard, shelters' capacity and desired number of the shelters to be located were identified. The model was solved by Exact Algorithm.

Rodriguez-Espindola and Gaytán [51] developed the bi-objective optimization model to define the appropriate location for shelters and distribution centers placement while simultaneously determining the inventory preposition of the goods. The objectives of the developed model aimed at minimizing the distance and a set of costs that combined the acquisition cost, transportation cost and facility location cost. The model was tested with a case study of the flood in Villahermosa, Mexico. In order to obtain the Pareto frontier, Weighted Sum Method was selected to solve the bi-objective optimization problem. Then, the obtained results from this study were compared with the existing guidelines announced by Mexican authorities.

Hu et al. [23] conducted the study on shelter site selection to respond to the earthquake in Beijing, China. The bi-objective model for minimizing the transportation distance and total cost of shelter construction was proposed. The Non-dominated Sorting Genetic Algorithm was employed to improve the performance of both effectiveness and efficiency.

Chanta and Sangsawang [10] formulated the bi-objective optimization model to define the proper locations for using as the temporary shelters. The first objective was to maximize the number of victims that can be covered by the open shelter within a fixed distance. The second objective was to minimize the total distance between the disrupted areas and the closest shelters. The Epsilon Constraint method was employed to address the conflict objective functions. The application of the proposed model was tested via the flood case study in Nonthaburi, Thailand.

Balcik and Beamon [2] formulated the model to determine the optimal number of distribution centers for storing the relief supplies. The selected distribution centers should be able to entirely satisfy the victims' demand. The transportation cost between the affected place and selected distribution center was restricted by the limited budget. The model was tested with the case study of worldwide earthquake occurrence during 1900 – 2006 and solved by the Exact Algorithm.

Manopiniwes and Irohara [35] proposed the multi-objective optimization model to define the location of relief facilities i.e. evacuation centers and distribution centers together with determining the stock preposition of the relief goods. In term of location-allocation, the objective functions were to minimize the fixed cost for opening distribution centers and cost of transportation. Another objective function attempted to minimize the maximum response time between facilities and demand points which included the threat areas and the selected evacuation centers. The normalized Weighted Sum

Method was applied to address the multi-objective functions. The application of the proposed model was validated based on a flood case study in Chiang Mai, Thailand.

The survey on related literature can be summarized to illustrate model formulations, solution methods and the applications of the proposed methodology are demonstrated in Table 2.1 and Table 2.2 respectively.

2.2 Research gap

Based on the literature review, the publications present the models for enhancing efficiency and effectiveness performances. For efficient criteria improvement, the objective functions of the formulated models usually seek to minimize the cost of transportation, fixed cost for opening the facilities, operating cost, and penalty cost. Whereas the effective criteria, the objective functions normally aim to minimize the distance between particular areas and selected facilities, traveling time, and the number of open facilities.

There were both single-stage and multi-stage location-allocations. In terms of the objective function, numerous publications focus on improving the single objective function. However, addressing the real-world problem requires to determine several important criteria together [13]. Some prior works improve both efficiency and effectiveness simultaneously which is the monetary and non-monetary term respectively, but the adopted solution methods require assigning the weight to define the importance of each objective function. For the victim's relief effort, allocated weight coefficients to incomparable criteria, especially monetary and non-monetary terms would be awkward to decision-making. It cannot signify and compare the importance of money and victim's welfare through weight allocation.

Capturing important data, information, and knowledge to formulate optimization models helps decision-makers to define proper relief facility location-allocation. Although optimization generates an optimal solution or near-optimal solution, sometimes requires a great computational time. The research relates location-allocation in humanitarian logistics or disaster management should be integrated with other decision support systems for sim-

Table 2.1: Literature review on model formulations and solution methods

Authors	Echelon	Model	Objectives func.		Facility types	Solution method
			Effectiveness	Efficiency		
Mete and Zabinsky [40]	Two	Single	Min travel time and unmet demand	Min operating cost	WH	EA
Mejia-Argueta et al. [39]	Single	Multi	Min max evacuation time Min max supply flow time	Min total cost	EF	WSM EC
Balcik and Beamon [2]	Single	Single	Max cover demand	-	DC	EA
Hallak et al. [20]	Single	Bi	Max cover demand	Min operating cost	S	WGP
Kongsomsaksakul and Yang [28]	Two	Single	Min evacuation time	-	S	GA
Qin et al. [50]	Single	Multi	Min distance Min weighted distance Min no. of shelters Min area for setting shelters	-	S	PSO
Barzinpour and Esmaeili [3]	Single	Bi	Max cover demand	Min logistics cost	EF	GP
Görmez et al. [16]	Two	Bi	Min demand weighted distance Min distanceMin no. of shelters	-	S	EC
Miç and Koyuncu [41]	Single	Multi	Max cover demand Max no. of facilities	Min total cost	HC	AHP WGP
Kanoun et al. [26]	Single	Single	Max. decision-makers' satisfaction	-	EF	WGP
Ozbay et al. [47]	Multi	Single	Min no. of shelters	-	S	EA
Burkart et al. [9]	Single	Bi	Min unmet demand	Min total cost	DC	EC
Kilci et al. [27]	Single	Single	Max min open shelters area	-	S	GIS
Boonmee et al. [7]	Single	Single	Min distance	-	S	EA Fuzzy AHP
Horner et al. [22]	Single	Single	-	Min transport cost	S	EA
Rodríguez-Espíndola and Gaytán [51]	Single	Bi	Min distance	Min total cost	S, DC	WSM
Horner and Downs [21]	Single	Single	-	Min transport cost	WH	GIS
Hu et al. [23]	Single	Bi	Min distance	Min cost of shelters	S	NSGA
Manopiniwes and Irohara [35]	Two	Single	Min max response time	Min total cost	S, DC	WSM
Lauras et al. [31]	Single	Single	-	Min transpot and logistics cost	WH	EA
Ma et al. [33]	Multi	Single	Min distance	Min total cost	WH	PSO
Chanta and Sangsawang [10]	Single	Bi	Max cover demand Min demand weighted distance	-	S	EC

Remark
S: Shelter
WH: Warehouse
DC: Distribution Center
EF: Emergency Facility

Table 2.2: Application of the facility location-allocation

Authors	Facility types	Disaster types	Characteristics of disaster	Case study
Mete and Zabinsky [40]	WH	E	Magnitude levels	Seattle, USA
Mejia-Argueta et al. [39]	EF	F	Simulated flood levels	Mexico
Balcik and Beamon [2]	DC	E	-	National Geophysical Data Center
Hallak et al. [20]	S	C	Vulnerability ratio	Idleb, Syria
Kongsomsaksakul and Yang [28]	S	F	-	Utah, USA
Qin et al. [50]	S	E	-	Beijing, China
Barzinpour and Esmaeili [3]	EF	C	-	Iran
Görmez et al. [16]	S	E	-	Istanbul, Turkey
Miç and Koyuncu [41]	HC	C	-	Syria
Kanoun et al. [26]	EF	C	-	Sfax, Tunisia
Ozbay et al. [47]	S	E	Aftershock scenario	Istanbul, Turkey
Burkart et al. [9]	DC	D	-	Mozambique
Kilci et al. [27]	S	E	-	Istanbul, Turkey
Boonmee et al. [6]	S	F	Flood warning alarm	Chiang Mail, Thailand
Horner et al. [22]	S	H	-	USA
Rodríguez-Espíndola and Gaytán [51]	S, DC	F	Flood level assessment	Villahermosa, Mexico
Horner and Downs [21]	WH	H	-	North Florida, USA
Hu et al. [23]	S	E	-	Beijing, Chi
Manopiniwes and Irohara [35]	S, DC	F	Flood risk scenario	Chiang Mai, Thailand
Lauras et al. [31]	WH	E	Magnitude levels	Peru
Ma et al. [33]	WH	E	-	Beijing ,Tianjin, Hebei, China
Chanta and Sangsawang [10]	S	F	-	Nonthaburi, Thailand

Remark:

C: Conflict area
D: Drought
E: Earthquake
F: Flood
H: Hurricane

plifying the practical use [36]. In this case, machine learning can employ to deal with location-allocation problem. The successes of using machine learning to solve this problem are proven via the study of Kuo et al., 2002 [29] which combines fuzzy AHP with ANN to define the proper location of convenience stores, and Yang et al., 2015 [60] that incorporates WebGIS with several machine learning algorithms i.e. ANN, support vector regression, linear regression, and boosted regression to predicting the sites to establish the hotels. Somehow, to the best of our knowledge, there still no prior works integrated optimization-based techniques with machine learning algorithms to tackle location-allocation under the context of humanitarian logistics.

Chapter 3

Efficient Shelter Location-allocation Model

3.1 Introduction

The proposed methodology begins with formulating an efficient shelter location-allocation model which involves cost control. Although humanitarian logistics aims at helping the affected people, somehow cost criterion is an important issue that should not be ignored. Moreover, it reflects how well the resource utilization. Without proper planning, the decision-makers would make the ad-hoc decision in which the scarce would occur and eventually affect the victims' welfare.

In this chapter, a mathematical model is proposed to minimize the total cost which includes fixed cost of opening the shelters, transportation cost for victim mobilizing, and service cost during the victims' stay in the shelter. The data that are used to formulate the model includes the candidate shelters which are predetermined, the number of victims in each affected area, traveling distance between the affected area and candidate shelter, shelters' capacity, fixed cost for opening shelters, victim's transportation cost, and duration of the disaster.

3.2 Model formulation

The preliminary parameter estimation, assumptions of the proposed model, model formulation, and decision variable are described as follows:

3.2.1 Preliminary parameter estimation

Distance estimation

Since coordinates of candidate shelters and affected are known. The Euclidean method is used to estimate the distance between two points.

Table 3.1: Distance between affected areas and candidate shelters

O/D	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
S1	11.81	15.99	18.04	20.12	11.26	11.24	11.24	25.55	9.00	10.33
S2	18.54	20.12	21.82	23.52	16.06	16.12	15.06	25.87	16.79	17.87
S3	20.27	13.15	12.25	11.43	15.33	15.48	13.73	4.40	23.80	22.97
S4	21.97	22.35	23.81	25.27	18.81	18.89	17.48	25.95	20.73	21.67
S5	14.81	17.95	19.88	21.84	13.41	13.42	12.93	26.04	12.37	13.63
S6	9.61	1.86	0.29	2.47	6.57	6.63	6.66	11.76	14.24	12.84
S7	19.86	12.07	10.56	9.05	15.47	15.60	14.29	1.10	24.00	22.88
S8	18.08	10.97	10.15	9.49	13.17	13.32	11.61	4.83	21.67	20.81
S9	25.26	18.81	18.21	17.59	20.10	20.26	18.26	9.65	28.15	27.61
S10	43.80	39.75	39.90	39.94	38.93	39.08	36.98	33.09	44.65	44.94
S11	23.29	17.09	16.64	16.22	18.12	18.28	16.25	9.34	26.08	25.57
S12	0.84	7.69	9.52	11.61	5.52	5.36	7.49	20.83	5.54	3.82
S13	3.70	5.09	6.65	8.63	5.03	4.91	6.82	18.21	8.60	6.93
S14	8.43	0.68	1.97	4.08	4.94	5.00	5.00	12.56	12.88	11.57
S15	11.52	4.17	2.08	0.82	8.92	8.97	9.02	10.91	16.29	14.80
S16	10.60	3.57	3.73	4.79	6.05	6.18	5.07	10.47	14.58	13.51
S17	10.25	2.62	2.36	3.56	6.19	6.29	5.63	10.68	14.52	13.31
S18	7.18	5.68	7.55	9.53	2.18	2.32	0.60	15.69	9.84	9.23
S19	23.51	15.63	13.74	11.73	19.67	19.78	18.76	4.74	28.00	26.70
S20	4.60	12.18	14.21	16.39	8.39	8.25	9.94	24.86	0.34	1.47

Constant coefficient of transportation cost

The constant coefficient of transportation cost per person varies on the distance is denoted by α. Herein, the α is estimated regarding the ratio of fuel cost per liter divided by the product of fuel consumption rate kilometer per liter and vehicle's capacity per trip as illustrated in equation 3.1.

$$\alpha = \frac{Fuel\ cost}{Fuel\ consumption\ rate \cdot Vehicle's\ capacity} \tag{3.1}$$

3.2.2 Model formulation

Assumptions

- The victims in each affected area are mobilized as an entire unit and not separately assigned to different shelters
- The number of victims and location of the candidate shelters are fixed
- The vehicles used in evacuation process are homogenous

Indices

I Set of affected area i

J Set of candidate shelter j

Parameters

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

c_j Capacity of the candidate shelter j

h_i Number of victims in area i

f_j Fixed cost of opening the shelter j

M Maximum acceptable distance between affected area and shelter

α Constant coefficient of transportation cost per kilometer per person

β Wage per person for hiring staff to work in the shelter

γ Ratio of the required staff per victims

T Duration of the disaster occurrence

Decision variable

X_j 1, if candidate shelter j is selected or otherwise 0

Y_{ij} 1, if affected area i is assigned to shelter j or otherwise 0

Z_{ij} The victim in area i is assigned to candidate shelter j

Objective function

$$Min \qquad \sum_{j\in J} X_j f_j + \alpha \sum_{i\in I}\sum_{j\in J} d_{ij} Y_{ij} h_i + \beta T \sum_{i\in I} \frac{Z_{ij}}{\gamma} \tag{3.2}$$

The objective function (3.2) attempt to minimize the total cost which includes three terms below.

$$\sum_{j\in J} X_j f_j$$

The first term involves the total fixed cost for opening the shelters, where where f_j is estimated regarding the installation cost of portable toilets, temporary warehouses, and kitchens.

$$\alpha \sum_{i\in I}\sum_{j\in J} d_{ij} Y_{ij} h_i$$

The second term explains the total cost for victims transportation. The transportation cost estimation is considered based on the distance and number of victims that are mobilized from affected area i to selected shelter j multiply by the constant coefficient of victims transportation cost varies on distance.

$$\beta T \sum_{i\in I} \frac{Z_{ij}}{\gamma}$$

The third term relates the service cost which occur during the stay of the victims. The estimation is performed based on the number of required staffs to work in the shelters during the disaster occurrence.

Subject to

$$\sum_{j \in J} Y_{ij} = \; 1, \quad \forall_{i \in I} \tag{3.3}$$

Constraint (3.3) identifies that an affected area i must be entirely assigned to only particular shelter j

$$Y_{ij} \;\; \leq \;\; X_j, \quad \forall_{i \in I, j \in J} \tag{3.4}$$

Constraint (3.4) restricts each affected area i will be allocated to only selected shelters.

$$d_{ij} Y_{ij} \;\; \leq \;\; M, \quad \forall_{i \in I, j \in J} \tag{3.5}$$

Constraint (3.5) limits the distance between an affected area i to selected shelter j does not exceed the maximum acceptable distance M.

$$\sum_{i \in I} Z_{ij} \;\; \leq \;\; c_j X_j, \quad \forall_{j \in J} \tag{3.6}$$

Constraint (3.6) ensures that the number of assigned victims does not exceed the capacity of selected shelter j.

$$\sum_{j \in J} Z_{ij} \quad = \quad h_i, \quad \forall_{i \in I} \tag{3.7}$$

Constraint (3.7) restrains the number of assigned victims equal to the number of victims in each affected area i.

$$X_j \quad \in \{0, 1\}, \quad \forall_{j \in J} \tag{3.8}$$

Constraint (3.8) defines the binary variable, X_j is 1 if candidate shelter is selected to open, otherwise 0.

$$Y_{ij} \quad \in \{0, 1\}, \quad \forall_{i \in I, j \in J} \tag{3.9}$$

Constraint (3.9) defines the binary variable, Y_{ij} is 1 if affected area i is allocated to candidate shelter j, otherwise 0.

3.3 Solution approach

The meta-heuristics search technique Genetic Algorithm (GA) is employed to solve the proposed model since it avoids getting trapped with the local optimal solution, and successfully used to deal with many location-allocation problems. Herein, the proposed model is solved in two aspects i.e. "capacitated shelter" and "uncapacitated shelter". With GA for shelter site selection and allocation, it starts with input the parameters of the model. The algorithm will begin to randomly initialize the population for generating the feasible solutions. Then, the fitness each individual population is measured based on the proposed objective function. Next, the value of fitness measure-

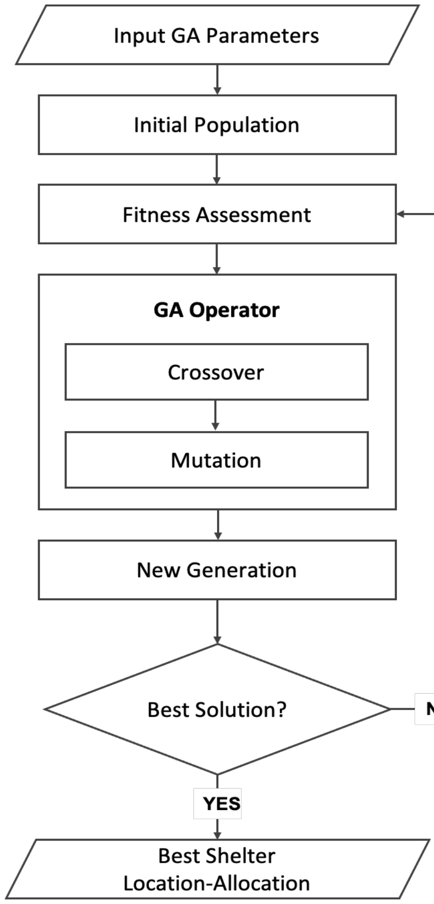


Figure 3.1: Flow chart of GA for shelter location-allocation

ment is passed through GA operator to crossover and mutate for producing the new population. After that, all individual populations are checked. Only the individual population that provides the best fitness value (herein the total cost) is selected as the final solution. Therein, the degree of constraint precision is set as 0.000001, convergence is 0.0001, random seed is 0, population size is 100, and GA is set to terminate if without any improvement longer than 30 sec.

3.4 Applicability of the proposed model

A case study of shelter allocation in response to flooding in Tha Uthae, Surat Thani of Thailand is applied to test the applicability of the proposed mathematical model. There is a set of predetermined shelters that must be justified which should be opened and assigned to serve all affected areas.

The terrain of Tha Uthae sub-district is lowland and repeatedly faces flooding, especially during the rainy season. Regarding the statistical data of the great flood in 2011 [53], there were a total number of 5,076 victims. Basically, the Department of Disaster Prevention and Mitigation, Ministry of Interior which is the government agency that decides the evacuation shelters for each community based on their administrative area. The candidate shelters are schools, colleges, city halls, or temples. However, the assigned shelters are rather decentralizing than centralizing. The number of victims in each affected area are and the candidate shelters are shown in Table 3.2-Table 3.3. Since the latitude and the longitude of affected areas and candidate shelters are known, the distances are estimated based on the Euclidean distance approach. The maximum acceptable distance between affected areas and shelters are assumed not to exceed 10 kilometers. The vehicles that are used for victim transportation belong to the Royal Thai Army. The truck capacity is 12 persons and the fuel consumption rate 8 kilometers per liter.

In terms of shelter's capacity, schools and colleges are assumed to handle the victims not over 2,000 victims as claimed by JICA [16], other shelters that are not the schools can accommodate 500 victims. The related costs for opening the shelters still need to be included, such as costs for portable toilets, tents to use as a temporary kitchen, medical center, and warehouse [14] which hereafter are defined as the fixed cost.

To estimate the service cost that occurs when serving the victims during the time they reside in the shelter, the cost of staff hire is determined. Although assisting the victims is volunteer work, government staffs are still paid by their agencies. In this case, the standard wage of 380 Thai Baht per person per day is taken into account. The number of required staff is 1 staff per 50 victims [14].

Table 3.2: Affected area and number of victims

Area	No. of victims (person)	Area	No. of victims (person)
A1	750	A6	250
A2	540	A7	350
A3	400	A8	450
A4	800	A9	500
A5	650	A10	386

Table 3.3: Candidate shelters and capacities

Candidate shelters	Capacity
S1, S3, S5, S6, S8, S10, S11 S14, S15, S16, S17, S19, S20	500
S2, S4, S7, S9, S12, S13, S18	2,000

3.5 Numerical experiment results

3.5.1 Computational results

Table 3.4 shows the results generated by the proposed model. The number of selected shelters, shelter allocation, and total cost of both capacitated and uncapacitated shelters are compared with the current shelter assignment announced by the government agency. "Capacitated shelter"considers the restrictions of capacity and that the maximum acceptance distance does not exceed 10 kilometers. There are 5 selected shelters—S7, S12, S18, S19, and S20—to serve the victims. The shelter utilization rates are 40%, 89.3%, 77%, 90%, and 100% respectively and the total cost is 899,471 Thai Baht.

For "uncapacitated shelter", the capacity in constraint 5 is ignored. It reveals that only small shelters which generate cheaper costs and are located within the acceptable distances of 10 kilometers are chosen. There are 3 selected shelters include S3, S6, and S20. The number of selected shelters and the total cost are less than that of the capacitated shelters. Since the objective function is not bound by the capacity restriction, the model then seeks to select a few shelters which are located in the acceptable distance

Table 3.4: The result of case study with acceptable distance not over 10 km

Affected area	Capacitate shelter	Uncapacitate shelter	Current plan
A1	S12	S20	S12
A2	S18	S6	S13
A3	S18	S6	S14
A4	S7	S6	S6
A5	S12	S20	S15
A6	S18	S20	S16
A7	S18	S20	S17
A8	S19	S3	S18
A9	S20	S20	S19
A10	S12	S20	S7
Setup cost (THB)	660,000	342,000	1,260,000
Transportation cost (THB)	6,911	6331	7,036
Service cost (THB)	232,560	232,560	232,560
Total cost (THB)	899,471	580,891	1,499,596

to minimize the total cost. The total cost of 3 selected shelters is 580,891 Thai Baht. However, uncapacitated shelters would be difficult to employ in a practical manner due to overabundantly assigning the victims to particular shelters, which leads to congestion and will eventually affect the victims' welfare.

Both capacitated and uncapacitated shelters are compared to the current shelter assignment planned by the government sector. The numerical experiment reveals that the service cost of all plans remain constant, as shown in Table 3.4, since the number of victims is not changed and all victims are rescued. Moreover, it is evident that the current plan fails to achieve cost efficiency because there are 10 shelters that are selected and allocated based on their administrative area. The shelter allocation is decentralized and causes the setup cost to be unavoidably higher. Likewise, the total cost obtained from the proposed model, both capacitated shelter and uncapacitated shelter is lower than the current plan as 40.02% and 61.26% respectively.

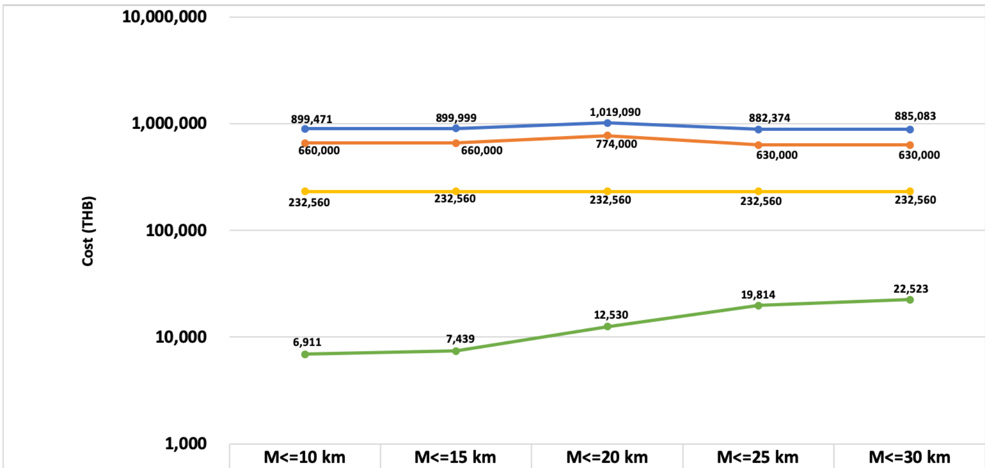
3.5.2 Sensitivity analysis

The sensitivity analysis is conducted to demonstrate how parameters influence the objective function and the model. Here, the maximum acceptable distances (constraint 3.5) are set between 10-30 kilometers to allow the numerical experiment to be more flexible. In the case of capacitated shelter, it is the most cost efficient when the maximum acceptable distance does not exceed 25 kilometers. It is required to select 5 shelters to serve the victims. Relaxing the maximum acceptable distance results in an increase in the transportation cost. On the contrary, the fixed cost of opening the shelter does not increase as the relaxed distance is extended. Meanwhile, the relaxation of distance will not significantly affect the service cost since the constraint strictly ensures that all victims are served thoroughly (Figure 3.2).

For uncapacitated shelter, it shows that, as the maximum acceptable distance is relaxed, the fixed cost of selected shelters decreases. This is because the relaxation of the acceptable distance means that the cheapest shelter can be found and selected without considering the limitation of the shelters' capacity. Since total cost is dominated by fixed cost, it leads the total cost to decrease as the maximum acceptable distance is relaxed (Figure 3.3).

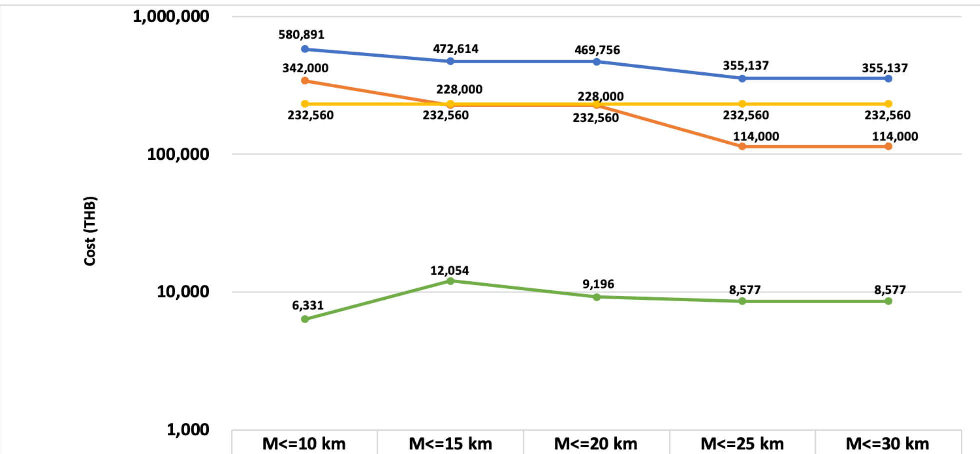
3.6 Conclusion and discussion

This chapter presents the mathematical model for shelter site selection and allocation for efficient response to relief logistics during the disaster. The model is formulated as mixed integer nonlinear programming and solved by Genetic Algorithm in order to achieve cost minimization. The proposed model is tested with the real world case study of the floods in Tha Uthae, Surat Thani, Thailand. The comparisons of the results obtained from this model (i.e. capacitated and uncapacitated shelter and current shelter allocation plan announced by the government) are shown. The comparison indicates that, when using the proposed model, the obtained results outperform the current shelter allocation plan. This study has positive implications



	M<=10 km	M<=15 km	M<=20 km	M<=25 km	M<=30 km
Total cost	899,471	899,999	1,019,090	882,374	885,083
Fixed cost	660,000	660,000	774,000	630,000	630,000
Transportation cost	6,911	7,439	12,530	19,814	22,523
Service cost	232,560	232,560	232,560	232,560	232,560
No. of selected shelter	5	5	6	5	5

Figure 3.2: Sensitivity analysis of capacitated shelter with distance 10-30 km



	M<=10 km	M<=15 km	M<=20 km	M<=25 km	M<=30 km
Total cost	580,891	472,614	469,756	355,137	355,137
Fixed cost	342,000	228,000	228,000	114,000	114,000
Transportation cost	6,331	12,054	9,196	8,577	8,577
Service cost	232,560	232,560	232,560	232,560	232,560
No. of selected shelter	3	2	2	1	1

Figure 3.3: Sensitivity analysis of uncapacitated shelter with distance 10-30 km

for the decision-makers to develop the appropriate strategies. However, this model still has the limitations because only cost criterion is concerned for shelter location-allocation. In practical manner, several important criteria should be included. Another limitation is that, the distance between affected areas and candidate shelters is approximated based on the Euclidean distance which could not perfectly reflect the actual road networks distance. However, these weak points are improved and extended to further study in the next model.

Chapter 4

Multi-objective Optimization Model for Shelter Location-allocation

4.1 Introduction

After disaster attacking, people's houses are likely to be destroyed, and the sufferers should be rescued from the disrupted points to the assigned shelters or evacuation centers. Decision-making of the relief facilities is very important, especially shelter site selection due to it affects to performance of humanitarian relief logistics in terms of equity, efficiency, and effectiveness [2, 34, 58]. Likewise, shelter placements require a considerable amount of money to invest and take a long-time effect on the related parties [47, 48]. With inappropriate determining the characteristics of relief requirements, the decision-makers could not make a suitable judgment which caused failure in healing the victims' suffer, high costs, waste of resources, and slow response. Furthermore, location-allocation also takes a significant impact on achieving proper practices in responding to disaster management [52].

Generally, the optimization techniques are employed to reasonably quantify the optimal number of required facilities and decide an appropriate location-allocation as well. Considering the previous works, the researchers usually proposed a single-echelon network and single-objective optimization (e.g.,[2, 26, 27, 22, 21, 31, 7]). However, to achieve practical purposes, several criteria should be simultaneously incorporated when formulating the model. It was revealed that, the researchers mainly developed the bi-objective optimization model when determining the relief facilities location-allocation (e.g., [5, 20, 3, 16, 9, 51, 23, 10]). There are relatively small numbers of the existing studies that proposed the multi-objective model (more than two objective functions) for dealing with location-allocation.

Regarding the reviewed literature, the objective functions are usually formulated to minimize transportation distance, transportation cost, transportation time. As a result, the nearest shelters or other facilities are selected eventually. However, it is suspicious whether the closest facilities are located far and safe enough from the areas that were attacked by the disaster. Selecting the nearest facilities seems to reduce time, distance, and cost but if not located far enough it will not be helpful for rescue and relief purposes.

For solution approaches, the previous works generally employed Weighted Sum Method [39, 51, 35]) and Weighted Goal Programming (e.g., [20, 3, 41, 26]) to decide the location-allocation of the relief facilities. Yet, Weighted Goal Programming requires the decision-makers to designate their preferences before the solution process. Nonetheless, the decision-makers only define their expectations without knowing beforehand what is included in the model [42], while Weighted Sum Method also involves defining the subjective preference through the weight coefficient for assigning to each objective function. The optimal solutions could be influenced if the weight coefficient of each objective is unclear determined by decision-makers [61]. Meanwhile, the Exact Algorithm requires a longer time for the computational process. The weak points of the aforementioned methods, especially assigning the weight to several criteria could confront the difficulty since some criteria are incomparable and troublesome to identify the priority, such as victims' welfare against monetary for healing [9] which should be considered when solving the problems in humanitarian logistics filed.

This study develops the multi-objective optimization model for justifying shelters location-allocation which considers both effective and efficient criteria. The proposed model encompasses contradiction objectives as follows:

1. Minimizing the total cost which combines fixed cost for opening shelters, victims transportation cost, and service cos
2. Minimizing the total evacuation time
3. Minimizing the number of selected shelters

The Epsilon Constraint method and Goal Programming are employed to define the compromising solutions. Unlike other prior works that usually restricted the traveling distance between an affected area and facility with the maximum distance. This study considers the minimum distance between an affected area and a candidate facility instead. The concept to evaluate minimum acceptable distance between the affected area and the selected shelter is introduced. The application of the proposed model is demonstrated through the case study of the flood in Tha Uthae Sub-district, Surat Thani, Thailand which normally confronts repeated floods, especially during the rainy season. The obtained results would be a benefit for the decision-makers to define and allocate the optimal number of shelters which generate the minimum total evacuation time with reasonable total cost. The parameters, assumptions, and model formulation are demonstrated in the next section.

4.2 Model formulation

The methodology of this research encompasses two phases i.e. preliminary parameter estimation, models formulation approach as follows:

4.2.1 Preliminary parameter estimation

In order to develop the model, the considerable parameters i.e. minimum acceptable distance between an affected area and candidate shelter (m_{ij}) is predetermined. The (m_{ij}) means the minimum distance between affected area i and candidate shelter j, which helps decision-makers avoid selecting shelters located nearest to affected areas. This is because the nearest shelters may not be safe from the same disaster. Initially, each affected area is divided into an equal grid of one-kilometer increments. The m_{ij} is simply estimated based on the diagonal length line of rectangle L, and multiplied by the ratio of victims in each affected area (h_i) to population density per square kilometer, as shown in equation (4.1)

$$m_{ij} = L \cdot \frac{h_i}{Population\ density} \tag{4.1}$$

4.2.2 Model formulation

Assumptions

The assumptions of the models are defined as below:

- The number of victims in each affected area is known and fixed
- The locations of all affected areas and candidate shelters are fixed
- The victims in each affected area are evacuated to the selected shelters as the entire unit and not permit to separately assign to different shelters
- The vehicles using in evacuation process are homogeneous
- The velocity of the vehicles is constant, the traffic conditions are ignored to consider

Mathematical model

There are three objectives functions, and a set of constraints for shelter location-allocation are demonstrated as follows:

Indices

I Set of affected areas

J Set of candidate shelters

Parameters

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

c_j Capacity of the candidate shelter j

h_i Number of victims in area i

f_j Fixed cost for opening the shelter j

m_{ij} Minimum distance between area i and shelter j

C Capacity of vehicle

N Number of vehicles for evacuation process

W Maximum allowed time for evacuating the victims from area i to shelter j

α Constant coefficient of transportation cost per kilometer per person

β Wage per person for hiring staff to work in the shelter

γ Ratio of the required staff per victim

T Duration of the disaster occurrence

V Velocity of the vehicle using in evacuation process

Decision variables

X_j 1, if candidate shelter j is selected or otherwise 0

Y_{ij} 1, if affected area i is assigned to shelter j or otherwise 0

Z_{ij} Number of victims in area i that are assigned to shelter j

Objective functions

$$Min \quad f_1 = \sum_{j \in J} X_j f_j + \alpha \sum_{i \in I} \sum_{j \in J} d_{ij} Y_{ij} h_i + \beta T \sum_{i \in I} \frac{Z_{ij}}{\gamma} \tag{4.2}$$

The first objective function (4.2) attempts to minimize the total cost that incorporates three terms. The first term is fixed cost for opening the shelters, where f_j is determined based on the cost for installing portable toilets, temporary warehouses, and kitchens. The second term is transportation cost regarding the distance and number of victims that are evacuated from affected area i to selected shelter j. The third term is the service cost which is estimated as the number of required staff to work in shelters throughout a disaster.

$$Min \quad f_2 = \sum_{i \in I} \sum_{j \in J} \frac{d_{ij} Y_{ij}}{V} \cdot \frac{hi}{NC} \tag{4.3}$$

The second objective function (4.3) seeks to minimize the total time for evacuating victims based on the distance between affected area i to shelter j, the number of victims that are displaced, the number of vehicles, the capacity of vehicles, and the vehicles' speed during the disaster.

$$Min \quad f_3 = \sum_{j \in J} X_j \tag{4.4}$$

The third objective function (4.4) aims to minimize the number of open shelters that can thoroughly serve the victims.

Subject to

$$\sum_{j \in J} Y_{ij} = \quad 1, \quad \forall_{i \in I} \tag{4.5}$$

Constraint (4.5) restricts that an affected area i must be entirely assigned to only single shelter j.

$$Y_{ij} \quad \leq \quad X_j, \quad \forall_{i \in I, j \in J} \tag{4.6}$$

Constraint (4.6) stipulates that affected area i must be assigned to only open shelters j.

$$d_{ij}Y_{ij} \quad \geq \quad m_{ij}, \quad \forall_{i \in I, j \in J} \tag{4.7}$$

Constraint (4.7) requires that the distance between affected area i to assigned shelter j must be farther than the minimum acceptable distance m_{ij}.

$$\frac{d_{ij}Y_{ij}}{V} \cdot \frac{hi}{NC} \leq W, \quad \forall_{i \in I, j \in J} \tag{4.8}$$

Constraint (4.8) limits the duration for evacuating victims from an affected area i to shelter j to no longer than the maximum allowed time for evacuating W (hours).

$$\sum_{i \in I} Z_{ij} \quad \leq \quad c_j X_j, \quad \forall_{j \in J} \tag{4.9}$$

Constraint (4.9) restricts the number of assigned victims to within the capacity of selected shelter j.

$$\sum_{j \in J} Z_{ij} \quad = \quad h_i, \quad \forall_{i \in I} \tag{4.10}$$

Constraint (4.10) ensures the number of assigned victims is equal to the number of victims in each affected area i.

$$X_j \quad \in \{0, 1\}, \quad \forall_{j \in J} \tag{4.11}$$

Constraint (4.11) is a binary variable: X_j is 1 if candidate shelter is selected to open; otherwise it is 0.

$$Y_{ij} \quad \in \{0,1\}, \quad \forall_{i \in I, j \in J} \tag{4.12}$$

Constraint (4.12) is a binary variable: Y_{ij} is 1 if affected area i is allocated to candidate shelter j; otherwise it is 0.

4.3 Solution approach

In practice, there are various criteria that should be considered when formulating the models for determining facility location-allocation. Dealing with multi-objective functions is more complex than single-objective functions in which the optimal solution can be acquired straightforwardly. Generally, multi-objective optimization is formulated by the equation (4.13) - (4.14).

$$Max \ or \ Min \qquad f(x) = (f_1(x), f_2(x), ..., f_p(x)) \tag{4.13}$$

Subject to

$$x \in F \tag{4.14}$$

Where p is the number of objective functions and $p \geq 2$, and $x = x_1, x_2, ..., x_n$ is the vector of decision variables, and S is a set of feasible solutions. In this case, the set of feasible solutions is recognized as the Pareto optimal set which is a compromise between various objectives, and there is no single optimal solution that can optimize all objective functions concurrently. As mentioned above, applying a solution approach which requires assigning a weighting coefficient to monetary and non-monetary objective functions is not appropriate in the context of humanitarian logistics. This study employs both priori and posteriori method in solving the proposed mathematical model. The Goal Programming (GP) without determining weight is a delegate of priori method while Epsilon Constraint method (EC) is a representative of posteriori method.

4.3.1 Epsilon Constraint method

In order to solve the proposed model, the EC proposed by Haimes et al. [19] is employed to generate the Pareto optimal. This is because this method does not require weight assignment and excludes the intervention of decision-makers. The decision-makers are allowed to evaluate and select the proper solution for implementation after the Pareto optimal is obtained [24]. With EC, only one objective function is selected as the primary objective function, while other objectives are transformed to be constraints of the main objective. However, the right-hand side value of each transformed constraint should be individually solved to obtain the optimal solutions for using as the epsilon value $\epsilon_2, \epsilon_3, ..., \epsilon_p$ [30, 38].

This study selects the first objective function (4.2) to be the primary objective because the inappropriateness of decision-making based on monetary criteria means that organizations could not properly allocate budget for relief purposes. Insufficient budget allocation would eventually affect victims' welfare. On the other hand, excessive spending reflects inefficiency of resource utilization. While the second (4.3) and third objective functions (4.4) are altered to be the constraints (4.16) and (4.17) respectively.

$$Min \quad f_1(x) \tag{4.15}$$

Subject to

$$f_2(x) \leq \epsilon_2 \tag{4.16}$$

$$f_3(x) \quad \leq \quad \epsilon_3 \tag{4.17}$$

(4.5) - (4.12)

4.3.2 Goal Programming

GP is a priori method in which the decision-makers identify optimistic preference values to each objective in advance. Since the aims of GP are to minimize deviations from preference values, the obtained solution is depended on decision-makers' desire consequently [13, 42]. Using GP to deal with multi-objective optimization in this study can be defined as the equation (4.18)-(4.23). Therein, d_i^+ *and* d_i^- are over-achievement and under-achievement of the objectives respectively. The preference level of objective i defined by decision-makers is denoted by g_i. In this case, g_1 is a preference value of total cost, g_2 is a preferred total evacuation time of 10 affected areas, and g_3 is a preference value of number of open shelters to thoroughly serve the victims. A set of feasible solutions is denoted as F.

$$Min \quad \sum_{i=1}^{p}(d_i^- \ + \ d_i^+) \tag{4.18}$$

Subject to

$$f_1(x) - d_1^+ + d_1^- = g_1 \tag{4.19}$$

$$f_2(x) - d_2^+ + d_2^- = g_2 \tag{4.20}$$

$$f_3(x) - d_3^+ + d_3^- = g_3 \tag{4.21}$$

$$x \in F \tag{4.22}$$

$$d_i^+, d_i^- \geq 0 \tag{4.23}$$

$$(4.5) - (4.12)$$

The numerical experiment is conducted by using What'sBest LINDO Optimization with laptop Microsoft Windows 10, Intel(R) Core (TM) 1.51 GHz, RAM 4.0 GB. The applicability of the proposed model is validated by the flood case study which is demonstrated in the next section.

4.4 Applicability of the proposed model

A case study of the flood in Tha Uthae, Surat Thani province of Thailand is adopted to this study. The terrain of Tha Uthae is lowland and usually faces with flooding, especially during the rainy season. Providing temporary shelters to serve the victims is one of the basic relief processes for responding to the disaster. Basically, the Ministry of Finance takes the responsibility to allocate the grant aid for responding to disaster relief and emergency assistance. Each district receives an initial aid of 500,000 THB per district, and also a budget to pay for meals and stuff. In summary, each district will receive an initial allowance of 1,300,000 baht regarding the Regulation of the Ministry of Finance on Government Grant for Relieving Disaster Victims in Emergencies 2020 [43]. For shelter site selection and allocation, the Department of Disaster Prevention and Mitigation, Ministry of Interior of Thailand is the agency that takes responsibility in this matter. The existing infrastructures such as colleges, schools, city halls, and temples are normally used as the candidate shelters. However, the current judgment on shelter site selection and allocation are rather decentralizing.

Based on the great flood of Tha Uthae in 2011, there were 5,076 victims that suffered from the submerged. At that time, the population density per square kilometer area was 120 persons. There were 10 affected areas and 20 candidate shelters for serving the sufferers [53]. Since coordinates of affected areas and candidate shelters are known, road network distances between the affected areas to candidate shelters can be acquired from the Google Maps Distance Matrix API. The vehicles that are used in victims' transportation belong to the Royal Thai Army. Herein, there are 5 vehicles available in each selected shelter. The vehicle's capacity is 12 persons, a fuel consumption rate is 8 kilometers per liter, and vehicle's speed during the inundation is 24 kilometers per hour based on the estimated function of flood depth and vehicle's speed proposed by Pregnolato et al.[49].

In the aspect of candidate shelter's capacity, colleges and schools can handle 2,000 victims [16]; others else can accommodate 500 victims. Fixed cost for opening shelter is determined regarding the expenses of portable toilets, and tents for using as temporary kitchen, medical center, and warehouse [14].

For a service cost that occurs when serving the victims during the time they residing in the shelters. A service cost is estimated based on cost of staff hiring. The government staffs are still paid by their agencies with the standard wage of 380 Thai Baht per person per day. The number of required staff is 1 staff per 50 victims [14]. Average duration of the disaster occurrence based on the historical data is 6 days, while the restricted times to finish evacuating all victims from a particular area to assigned shelter are set from 64 to 84 hours. Table 4.1 - 4.2 shows the parameters that are used in the numerical experiment.

Table 4.1: Affected area and number of victims

Area	No. of victims (person)	Aarea	No. of victims (person)
A1	750	A6	250
A2	540	A7	350
A3	400	A8	450
A4	800	A9	500
A5	650	A10	386

Table 4.2: Candidate shelters and capacities

Candidate shelters	Capacity
S1, S3, S5, S6, S8, S10, S11 S14, S15, S16, S17, S19, S20	500
S2, S4, S7, S9, S12, S13, S18	2,000

4.5 Numerical experiment results

Initially, the proposed model is solved by EC and GP with the maximum allowed time for evacuating victims as 72 hours ($W = 72$) due to the relief organization should respond to disasters within the first 3 days after occurrence. The results generated by EC and GP are then compared with the current shelter location-allocation plan.

4.5.1 Numerical experiment results generate by Epsilon Constraint method

First, the three objective functions are solved individually. The optimal solution of each objective function is then used to construct the Payoff Table to illustrate the lower bound and upper bound (Table 4.3). These bounds are known as the ϵ_2 and ϵ_2 of the additional constraints of equation (4.16) and (4.17) respectively.

Based on solving the multi-objective optimization with EC, the Pareto optimal and shelter location-allocation is shown in Table 4.4. When concurrently considering three criteria for dealing with shelter location-allocation problems, total cost and number of selected shelters remain the same, at 869,944 Thai baht and 4 shelters respectively. However, total time for evacuating victims from 10 affected areas to selected shelters is 203.07 hours, which is a considerable improvement.

Table 4.3: Payoff table under the standard evacuation time 72 hours

Criteria	Objective functions			Lower bound	Upper bound
	f_1	f_2	f_3		
Total cost	**869,944**	1,002,712	880,925	869,944	1,002,712
Total evacuation time	338.46	**244.78**	227.48	227.48	338.46
Number of shelters	4	5	**4**	4	5

Table 4.4: Pareto optimal and shelter allocation generated by Epsilon Constraint method

Total cost (THB)	Total evacuation time (Hours)	Number of shelters (Shelters)	Shelter-allocation
869,944	203.07	4	S1: A8 S2: A4, A6, A7, A9 S4: A1, A2, A5 S13: A3, A10

4.5.2 Numerical experiment results generate by Goal Programming

When solving the multi-objective for shelter location-allocation problem by GP, the goal is set to minimize total deviations from the preference values of three objective functions. However, each objective function is a different criterion, i.e., cost, time, and unit of shelter, the deviation of which cannot be directly considered together. Therefore, the deviation is considered in terms of "percentage deviation". Under the maximum allowed time for evacuating of 72 hours ($W = 72$), it generates a total percentage deviation of 1.02. The total cost for opening shelters, victim transportation cost, and service, was 1,030,898 Thai baht. The total time for evacuating all victims from 10 affected area is 401.25 hours. In this case, there are 5 shelters selected to serve the victims (Table 4.5).

Table 4.5: Pareto optimal and shelter allocation generated by Goal Programming

Sum Deviation	Total cost (THB)	Total evacuation time (Hours)	Number of shelters (Shelters)	Shelter allocation
1.02	1,030,898	401.25	5	S1: A9 S2: A5, A6, A7, A8 S4: A1, A4 S7: A2 S13: A3, A10

4.5.3 Comparisons of the Pareto optimal generated by Epsilon Constraint and Goal Programming

The Pareto optimal generated by EC and GP are compared with the current shelter location-allocation plan. The comparisons reveal that solving the proposed model with EC and GP outperformed the current plan in terms of total cost and number of open shelters. The current shelter location-allocation plan revealed the best total evacuation time. The current plan opened several shelters to serve the victims, helping to reduce transportation time and distance. However, the allocated budget for responding to the emergency situation is only 1,300,000 Thai baht [43], which would not be enough to enact this plan (Table 4.6).

This study also conducts sensitivity analysis to investigate how the parameters affect the objective functions. The experiment results are illustrated in the next section.

4.5.4 Sensitivity analysis

The sensitivity analysis is conducted to both Epsilon Constraint method and Goal Programming to observe how the objective functions change when a particular parameter is relaxed. In this analysis, the maximum allowed time for evacuating the victims from affected area i to selected shelter j was relaxed to between 64-84 hours (W = 64-84). The numerical experiments are demonstrated as follows:

Table 4.6: Comparison results generated by each solution approach

Criteria	Solution approach		
	Epsilon Constraint	Goal Programming	Current Plan
Total cost (THB)	869,944	1,030,898	1,546,126
Total evacuation time (Hours)	203.07	401.25	198.39
Number of shelters (Shelter)	4	5	10
Shelter allocation	S1: A8 S2: A4, A6, A7, A9 S4: A1, A2, A5 S13: A3, A10	S1: A9 S2: A5, A6, A7, A8 S4: A1, A4 S7: A2 S13: A3, A10	S6: A4 S7: A10 S12: A1 S13: A2 S14: A3 S15: A5 S16: A6 S17: A7 S18: A8 S19: A9

Sensitivity analysis based on Epsilon Constraint Method

When maximum allowed times for evacuating are relaxed to be longer, the total costs and the number of open shelters do not decrease. Sensitivity analysis results indicate that if decision-makers seek to minimize total cost, setting $W = 72$ hours would be the proper policy. On the other hand, if decision-makers put more importance on improving total evacuation time, the appropriate value of W would be 66, 68, or 70 hours. Although setting W as 66 hours generated the lowest total time of victims' evacuation (155.62 hours), it required a large number of opened shelters, leading to the highest total cost, at 1,076,591 Thai baht (Table 4.7).

Sensitivity analysis based on Goal Programming

Relaxing maximum allowed times for evacuating victims from each area to selected shelters does not improve total cost or number of open shelters. If decision-makers seek to minimize total cost and number of open shelters with acceptable total victim evacuation time, setting $W = 68$ hours would satisfy these requirements. Furthermore, the results of sensitivity analysis indicate that, defining W to be longer than the standard 72 hours for time of victim evacuation would not improve total cost, evacuation time, or number of open shelters (Table 4.7).

Comparisons of sensitivity analysis generated by each solution

In terms of total cost, the results generated by EC and GP are compared with the total cost of the current shelter location-allocation plan. Even when W is relaxed, the total cost of the current plan is fixed as 1.55 million Thai baht, due to the fact that shelter location-allocation is only based on administrative areas but W is not considered. This numerical experiment reveals that solving the proposed mathematical model with EC and GP produces lower costs than the current plan, and the results generated by EC outperform those of GP (Figure 4.1).

For total evacuation time of 10 affected areas, employing the current plan for shelter assignment produces a total evacuation time of 198.9 hours, which is quite low due to the large number of shelters opened to serve the victims. However, it was found that the results produced by EC were better than the current plan when relaxing W to 66,68, or 70 hours, while GP generated total evacuation times above 350 for all W values (Figure 4.2).

Considering the number of open shelters, the current plan assigned 10 shelters to serve 10 affected areas, even after relaxing W, which led to the results generated by EC and GP outperforming the current plan. Overall, the results produced by EC generated a lower number of open shelters than GP, except when W is relaxed to 66 or 68 hours (Figure 4.3).

Table 4.7: Sensitivity analysis of shelter allocation varies on solution approaches and restriction time

Restriction time (Hours)	**Epsilon Constraint**			**Goal Programming**		
	Total cost (THB)	Total evacuation time (Hours)	No. of shelter (Shelter)	Total cost (THB)	Total evacuation time (Hours)	No. of shelter (Shelter)
64	870,156	203.55	4	1,138,103	376.08	6
66	1,076,591	155.62	6	1,116,466	407.06	6
68	971,278	174.93	5	1,027,263	387.79	5
70	971,278	174.93	5	1,145,278	402.66	6
72	869,944	203.07	4	1,030,898	401.25	5
74	870,003	203.21	4	1,097,109	446.48	6
76	870,003	203.21	4	1,124,218	435.77	6
78	989,294	214.96	5	1,119,288	417.51	6
80	880,772	227.14	4	1,112,978	394.14	6
82	873,731	211.49	4	1,230,341	406.59	7
84	873,731	211.49	4	1,230,763	408.16	7

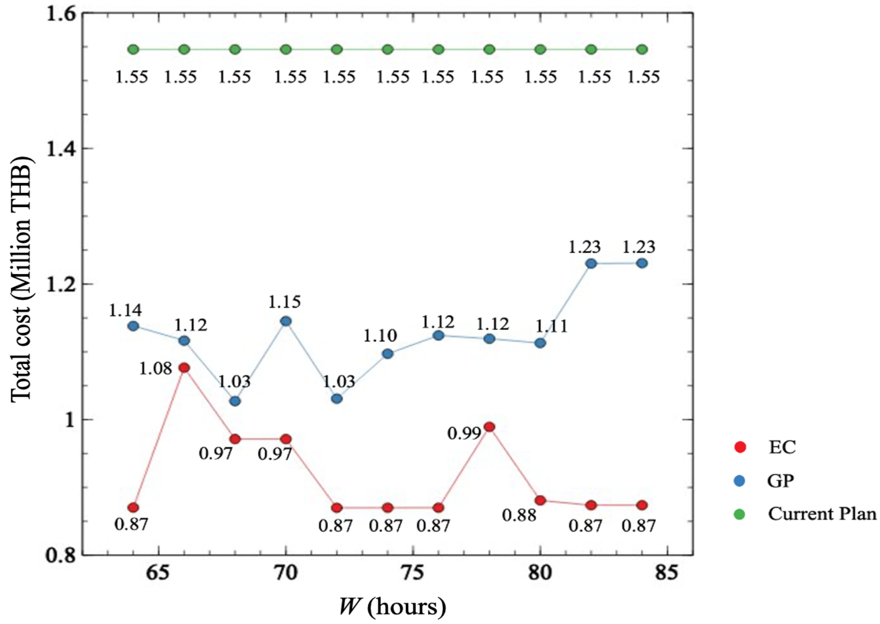


Figure 4.1: Comparisons of total cost generated by Epsilon Constraint and Goal Programming

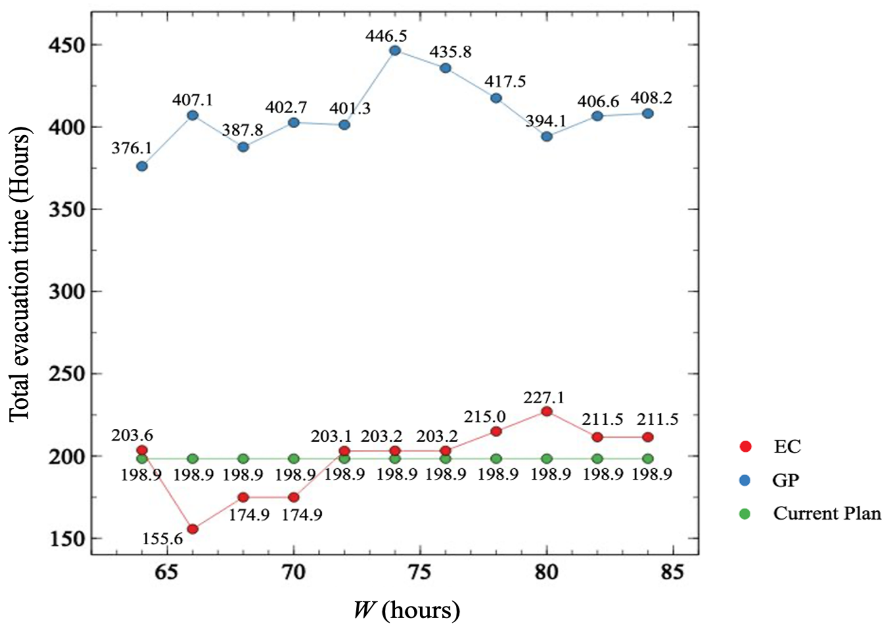


Figure 4.2: Comparisons of total evacuation time generated by Epsilon Constraint and Goal Programming

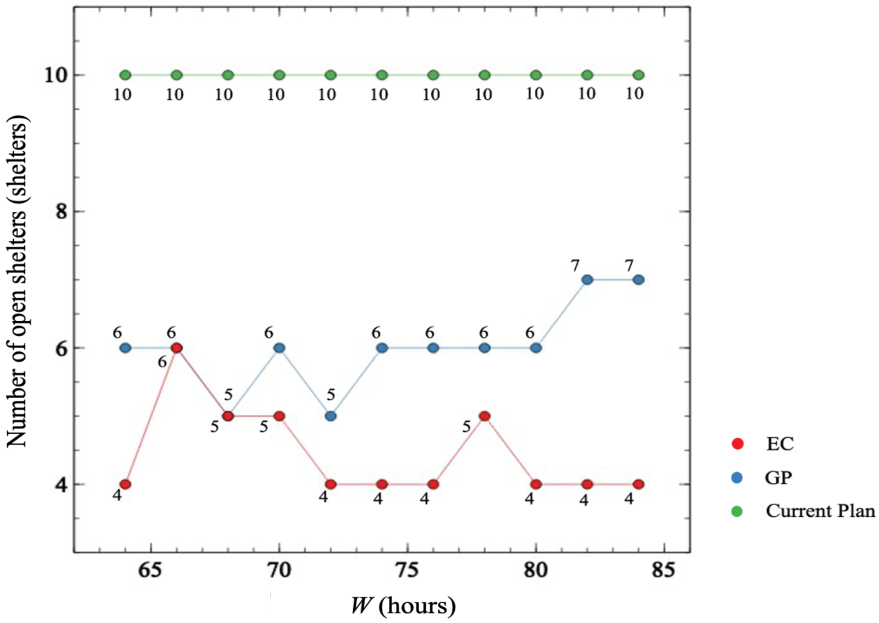


Figure 4.3: Comparisons of number of selected shelters generated by Epsilon Constraint and Goal Programming

4.6 Conclusion

This study proposes the multi-objective optimization model for shelter location-allocation in order to improve humanitarian relief logistics. There are three objective functions: to minimize total cost, total evacuation time, and number of open shelters. The Epsilon Constraint and Goal Programming are used to solve the proposed mathematical model. Moreover, sensitivity analysis is conducted to observe the impact of a parameter (maximum allowed time for evacuating) on the objective function. The optimal solutions generated by Epsilon Constraint and Goal Programming are compared with the current shelter location-allocation plan. The application of the proposed model is validated through a case study of shelter location-allocation in response to flooding in Tha Uthae, Surat Thani, Thailand. The numerical experiment results, in terms of total cost and number of open shelters generated by solving the proposed model, clearly outperform the current shelter location-allocation plan. On the other hand, the current plan mainly produces a better total evacuation time, due to a higher number of shelters open to serve victims.

Considering the solution approaches, i.e. Epsilon Constraint and Goal Programming, numerical experiments demonstrate that Epsilon Constraint proves more informative than Goal Programming when making a decision on shelter location-allocation, since Goal Programming seeks to minimize deviation from preference values of all objective functions. It can be stated that preference values defined by decision-makers influence the optimal solution and the performance of humanitarian logistics. However, solving the proposed model with these solutions can improve decision-making in response to disasters, especially flooding.

The limitation of this study involves the application of other disaster types. The proposed model perhaps work well in case of flood problems in which the characteristics of disaster are unlike other catastrophes e.g. earthquake, hurricane, or landslide. Currently, decision-making on facility location-allocation in response to disasters is usually conducted based on decision-makers' experience or ad-hoc decision-making. Thus, the proposed model would improve both efficiency and effectiveness of humanitarian relief logistics. The findings of this study provide a guideline to improve decision-making for shelter location-allocation in the context of humanitarian logistics, and would be advantageous for designing a proper disaster response strategy in the future.

Chapter 5

A Novel Approach for Determining Shelter Location-allocation in Humanitarian Relief Logistics

5.1 Introduction

Disaster onsets occur more frequently and impact humankind and economic system all over the world. In 2019, there were 95 million affected people, 11,755 number of deaths, and resulted in an economic loss of $103 billion approximately [11]. Humanitarian logistics takes a significant role in supporting disaster management processes by managing the flows of basic aid such as foods, water, survival bags, and medical supplies [58, 59] with the right quantity, time, and place for helping people [34, 54]. It also relates evacuating the victims from affected areas to safe areas. Decision-making on location-allocation of relief facilities such as shelter, medical centers, distribution centers, warehouses, etc. is important. Among all relief facilities, shelter location-allocation is the critical part because it influences the security and welfare of the sufferers and impacts the performance of humanitarian logistics [47]. Although dealing with catastrophes is such uncertainty, but having decision support helps in defining the measures for minimizing loss of life and damages [25]. Previously, a large number of researchers employ optimization techniques to justify relief facilities location-allocation with the efforts to improve effectiveness, efficiency, and equity. The necessary data that incorporate in the optimization including location of damaged areas and candidate facilities, number of victims, distance, time, cost, resource for rescue process, magnitude of disaster, etc. [48]. Recently, machine learning algorithms (ML) can be integrated to select the location of potential facilities such as hotels and convenience stores [29]. Nevertheless, to the best of our knowledge, integrate ML algorithm for determining facilities location-allocation in the context of humanitarian logistics is somehow not existing.

This study proposes a methodology that integrates the Epsilon Constraint method (EC) and Artificial Neural Network (ANN) to determine shelter location-allocation. Since shelter location-allocation is a critical part of disaster response stage, fast decision-making is very important. A multi-objective optimization model is formulated to simultaneously minimize total cost and minimize total evacuation time. The proposed model is solved by Epsilon Constraint method because it generates the optimal solutions without intervention of decision-makers during the solution process. However, Epsilon Constraint method requires intensive computational time, especially when dealing with large-scale data and with several objective functions. Thus, ANN is combined with Epsilon Constraint method to facilitate prompt decision-making and address the complexity. Herein, ANN is supervised by the optimal solutions generated by Epsilon Constraint method. The applicability of the proposed methodology is demonstrated through a case study of shelter allocation in response to flooding in Surat Thani, Thailand. It is plausible to use this proposed methodology to improve disaster response for the benefit of victims and decision-makers.

5.2 Related work

5.2.1 Optimization-based for facility location-allocation

There are many studies that determine the appropriate location-allocation of the relief facilities to prepare and respond to humanitarian logistics. The relief facilities for supporting pre and post-disaster management include shelters, medical centers, healthcare centers, warehouses, distribution centers, disease control centers, and garbage dumps. The decision-making on facilities location-allocation is usually done based on optimization methods. The existing pieces of literature encompass a single echelon and multi-echelon which represented through single-objective and multi-objective optimization model. Although dealing with several objectives or criteria together is difficult, especially when each objective is opposed but it is a necessity when conducting decision-making in practice [45].

For shelter location-allocation, majority of the prior works usually present a single echelon with both single and multi-objective. In aspect of single-objective optimization, the authors propose the models to improve either efficiency or effectiveness such as minimizing transportation cost and solve by exact algorithm [22], minimizing total cost then solve by Genetic Algorithm [48], minimizing distance between disrupted areas and shelters [7], minimizing number of opened shelter and solve by Exact Algorithm [47]. For the multi-objective model, some studies just seek to improve an effective criterion such as minimizing demand weighted distance, number of shelters, and area for locating shelter, then solve the proposed model by Particle Swarm Algorithm [50], minimizing demand weighted distance, number of shelters and employs Epsilon Constraint method for a trade-off [16], maximizing demand coverage while minimizing demand weighted distance, then solve by Epsilon Constraint method [10]. However, there are still some works attempt trading-off between efficiency and effectiveness criteria by minimizing maximum response time and total cost, and solve by Weighted Sum Method [37], maximizing demand coverage while minimizing operation cost and employs Weighted Goal Programming to solve the proposed model [20], minimizing distance and total cost, then solve by Weighted Sum method [51].

5.2.2 Machine learning for facility location-allocation

ML can be combined with other applications for facility location-allocation. There is a study that employs K-means to determine the capacitated facility location-allocation. The proposed clustering-based approach is compared against the Genetic Algorithm [32]. There also integration between an automated WebGIS with ANN, Support Vector Regression, Linear Regression and Boosted Regression for predicting the potential sites to establish the hotels [60]. Moreover, ANN is also combined with Fuzzy AHP to construct a decision support system for convenience stores location-allocation [29]. Despite there are a relatively small number of studies adopt ML to justify the proper location, but it implies the applicability ML in determining location-allocation problem, and still room for further studies.

ANN is one of ML algorithms that is used for coping with location-allocation problems. It mimics the biological nervous system of human brain's activities in which much more complex than the normal model can capture [55]. It is recognized as a tool for classifying the patterned or structured of dataset [4]. The architecture of ANN encompasses three parts i.e. input layer, hidden layers, and output layer. The input layer correlates with storing input data, information, or feature which required a normalization beforehand for a better numerical precision purpose. The hidden layer is an internal layer consists of neurons for extracting associated patterns of the processes being analyzed. The output layer includes the neurons to generate and present the final network outputs [12]. The architecture of ANN is shown in Figure 5.1

Regarding the literature survey, the studies on location-allocation are mostly conducted based on an optimization basis. Some studies simultaneously incorporate efficiency and effectiveness which is monetary and non-monetary respectively. The solution methods for dealing with these criteria involve weighted assignment to signify the importance of a particular objective function, especially Weighted Sum method and Weighed Goal Pro-

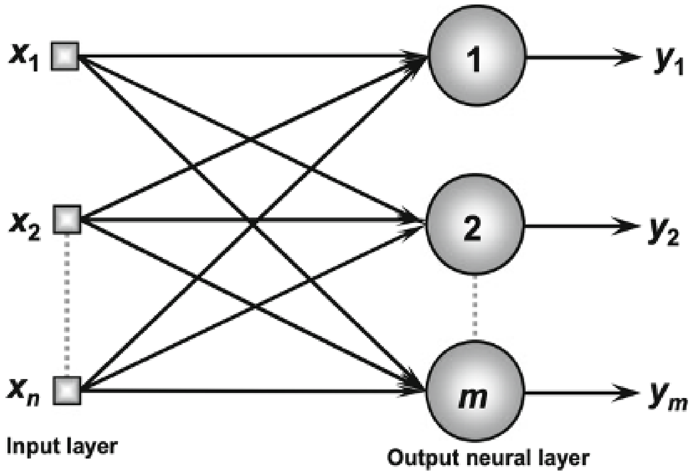


Figure 5.1: Architecture of single ANN [12]

gramming. Nevertheless, monetary and non-monetary terms cannot compare in this sense. Decision-makers cannot state that money is more important than victims' welfare since humanitarian logistics aims at helping people with reasonable resource utilization. Therefore, the solution approaches relate to weighed assignment would not appropriate for this context. The obtained results from solving optimization model guarantee the optimal solution or near-optimal solution. Somehow, the numerical experiment processes are conducted under the assumption that all areas are attacked by disaster concurrently, and a particular facility can serve several areas. Though in a real situation, the onset would not arise at the same time and there would be some areas that disrupted. The onsets of target areas could happen in numerous patterns and more complex. So, this weak point can be coped with ML algorithm for decision making on location-allocation problems.

5.3 Model formulation

This study begins with formulating a multi-objective optimization model to simultaneously minimize total cost and minimize total evacuation time.

The necessary data for developing the model including number of victims, locations of affected areas and candidate shelters, distance based on road networks obtained from Google APIs, vehicle specifications, restricted time for evacuation, and ratio of required staff. Formulation of multi-objective optimization model for shelter location-allocation is illustrated as follows:

Assumptions

- The locations of all affected areas and candidate shelters are fixed
- The victims in each affected area are evacuated to the selected shelters as the entire unit and not permit to separately assign to different shelters
- The vehicles using in evacuation process are homogeneous
- The velocity of the vehicles is constant, the traffic conditions are ignored to consider

Indices

I	Set of affected areas
J	Set of candidate shelters

Parameters

d_{ij}	Distance between affected area i and candidate shelter j
Cap_j	Capacity of candidate shelter j
Cap_v	Capacity of vehicle
h_i	Number of victims in area i
f_j	Fixed cost for opening the shelter j
m_{ij}	Minimum distance between affected area i and candidate shelter j
N	Number of vehicles for evacuation process
T	Duration of the disaster occurrence
V	Velocity of the vehicle using in evacuation process
W	Time for evacuating the victims in area i to shelter j

α Constant coefficient of transportation cost per kilometer per person

β Wage per person for hiring staff to work in the shelter

γ Ratio of the required staff per victim

Decision variables

X_j 1, if candidate shelter j is selected or otherwise 0

Y_{ij} 1, if affected area i is assigned to shelter j or otherwise 0

Z_{ij} Number of victims in area i that assigned to shelter j or otherwise 0

Objective functions

$$Min \quad f_1 = \sum_{j \in J} X_j f_j + \alpha \sum_{i \in I} \sum_{j \in J} d_{ij} Y_{ij} h_i + \beta T \sum_{i \in I} \frac{Z_{ij}}{\gamma} \tag{5.1}$$

The first objective function (5.1) is formulated to minimize the total cost that includes fixed cost for opening shelters, victim's transportation cost which is determined based on the number of victims and distance between affected areas and selected shelters, and operation cost which is paid for serving the victims during their stays in the shelters.

$$Min \quad f_2 = \sum_{i \in I} \sum_{j \in J} \frac{d_{ij} Y_{ij}}{V} \cdot \frac{h_i}{NCap_v} \tag{5.2}$$

The second objective function (5.2) attempts to minimize the total time for victims' evacuation which is estimated regarding the number of evacuated victims, distance between affected areas and selected shelters, number of available vehicles, capacity of vehicle, and speed of vehicle.

Subject to

$$\sum_{j \in J} Y_{ij} = \quad 1, \quad \forall_{i \in I} \tag{5.3}$$

Constraint (5.3) forces each affected area should be wholly allocated to only single shelter.

$$Y_{ij} \quad \leq \quad X_j, \quad \forall_{i \in I, j \in J} \tag{5.4}$$

Constraint (5.4) restricts each affected area should be allocated to only opened shelter.

$$d_{ij} Y_{ij} \quad \geq \quad m_{ij}, \quad \forall_{i \in I, j \in J} \tag{5.5}$$

Constraint (5.5) restrains the distance between affected area and selected shelter must be greater than the ideal minimum distance to ensure that selected shelter is far enough from the attacking point which could occur in area i.

$$\frac{d_{ij} Y_{ij}}{V} \cdot \frac{h_i}{NCap_v} \leq W, \quad \forall_{i \in I, j \in J} \tag{5.6}$$

Constraint (5.6) limits the victim's evacuation in each affected area to selected shelter must not exceed the restricted time.

$$\sum_{i \in I} Z_{ij} \quad \leq \quad Cap_j X_j, \quad \forall_{j \in J} \tag{5.7}$$

Constraint (5.7) restricts the number of assigned victims must not exceed the capacity of selected shelter.

$$\sum_{j \in J} Z_{ij} \quad = \quad h_i, \quad \forall_{i \in I} \tag{5.8}$$

Constraint (5.8) restrains the numbers of assigned victims equal to number of victims in each affected area.

$$X_j \quad \in \{0, 1\}, \quad \forall_{j \in J} \tag{5.9}$$

Constraint (5.9) expresses the binary variable X_j is 1 if candidate shelter is selected to open.

$$Y_{ij} \quad \in \{0, 1\}, \quad \forall_{i \in I, j \in J} \tag{5.10}$$

Constraint (5.10) defines the binary variable Y_{ij} is 1 if affected area i is allocated to shelter j, otherwise 0.

5.4 Proposed solution approach

Initially, the Epsilon Constraint approach proposed by Haimes et al. [19] is employed to solve the proposed multi-objective optimization model because the Pareto optimal can be obtained without intervention of decision-makers during the computational process. However, this method requires a greater execution time which could not effectively support disaster response. Hence, ANN is used to combine with Epsilon Constraint method in order to simplify fast decision-making. In this case, ANN learns the knowledge from the optimal solutions generated by Epsilon Constraint method. The solution approach is illustrated in Figure 5.2.

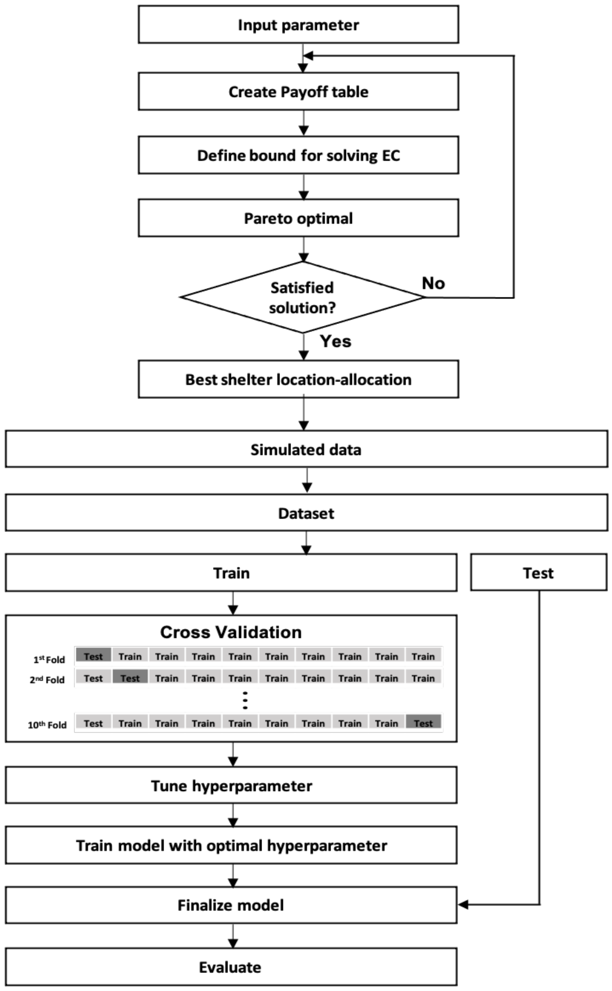


Figure 5.2: ANN-EC for shelter location allocation

5.4.1 Epsilon Constraint method for multi-objective optimization

Solving the proposed multi-objective optimization model with Epsilon Constraint method, only one objective function is assigned as the main objective while other objectives are transformed to be the additional constraints. Herein, f_1 which seeks to minimize the total cost is defined as the main objective function, while f_2 that aims to minimize the total time for victims' evacuation is transformed to be an additional constraint. Initially, f_2 is individually solved to produce the epsilon values (ϵ) to restrict the main objective. However, ϵ values must be defined appropriately to avoid generating inefficient solutions. Augmented objective function with positive coefficient constant helps to cope with inefficient solutions problem [16]. Thus, this study applies the allowance time to augment the f_2. The allowance is an additional time that could occur when conducting a specific task. It includes personal desire, fatigue, and delay caused by special situations. The personal desire is time to permit the staff to relax by drinking water, accessing restroom, etc. The fatigue is justified based on exhaustion and mental strength of staff. The delay is an additional time for transportation delay caused by disasters [44]. The allowance time of three factors is estimated as a total of 20% of the ordinary victim's evacuation time which denoted as δ. Solving a multi-objective optimization based on Epsilon Constraint can be illustrated below.

Objective function

$$Min \quad f_1 \tag{5.11}$$

Subject to

$$\delta \sum_{i \in I} \sum_{j \in J} \frac{d_{ij} Y_{ij}}{V} \cdot \frac{h_i}{NC} \quad \leq \quad \epsilon_{f_2} \tag{5.12}$$

(5.3) - (5.10)

The numerical experiment is conducted by using What'sBest LINDO Optimization with laptop Microsoft Windows 10, Intel(R) Core (TM) 1.51 GHz, RAM 4.0 GB.

Typically, the proposed model is deterministic and incorporates parameters that occurred in a specific year, all areas are assumed to confront disaster onsets concurrently. Shelter allocation is rather centralization in which all affected areas are probably assigned to share the same shelters. Nevertheless, all areas would not be attacked by disaster at the same time. The onsets perhaps occur in several ways such as affected areas A1-A5 were ever disrupted by disaster simultaneously. Affected areas A1-A4 were assigned to serve by shelter S4, while A5 is assigned to serve by S2. On the other hand, if only area A1 is attacked by disaster while A2 is safe, then it is arguable that what shelter should be assigned to serve A1. The proposed methodology must have the ability to deal with complexity. Therefore, the optimal solutions generated by Epsilon Constraint method are simulated into several situations in order to allow ANN to learn the knowledge of shelter location-allocation based on disaster onsets' patterns. The simulated data are generated for all possible combinations of the onsets and shelters assignment based on the optimal solutions obtained by solving the proposed model by Epsilon Constraint method. Herein, 0 means usual situation while 1 means attacked by disaster. The concept to simulate the dataset is shown in Figure 5.3.

Assigned shelter	Affected area				
	A1	A2	A3	A4	A5
S1					
S2					/
S3					
S4	/	/	/	/	
S5					

No.	A1	A2	A3	A4	A5	Assigned shelter
1	0	0	0	0	1	S2
2	1	0	0	0	0	S4
3	1	1	0	0	0	S4
4	1	0	1	0	0	S4
5	1	0	0	1	0	S4
6	0	1	0	0	0	S4
7	0	1	1	0	0	S4
8	0	1	0	1	0	S4
9	0	1	1	1	0	S4
10	0	0	1	0	0	S4
11	0	0	1	1	0	S4
12	0	0	0	1	0	S4
13	1	1	1	1	0	S4

Figure 5.3: The concept of simulating dataset based on obtained optimal solutions

5.4.2 ANN for shelter location-allocation

After the optimal solutions produced by Epsilon Constraint are simulated to express several disaster onsets together with shelter location-allocation, the ANN is employed to predict shelter assignment. Integrating ANN with Epsilon Constraint is beneficial to decision-making process because it helps to reduce the computational time and support fast decision-making. In order to deal with limited datasets and avoid bias from splitting train and test procedure, 10-fold cross-validation technique is introduced to check the effectiveness of ANN. Then, the data are trained and tested with feedforward ANN. The input layer represents the affected areas and shelter location-allocation. The output layer expresses result of ANN by aggregating the outputs from hidden layer via linear transfer function or summation function (5.13). Where n is total number of nodes and x_i is input multiplied by weight w_i and sum up with the bias value b.

$$\sum_{i=1}^{n} x_i w_i + b \tag{5.13}$$

The hidden layer lays between input and output layers to produce the outputs by determining the output from the prior layer with weights and biases. The obtained nonlinear is then transformed by using the Sigmoid function as illustrates in equation (5.14).

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \tag{5.14}$$

For the hyperparameter tuning step, this study adjusts the learning rate because it is the most important hyperparameter [15]. However, the optimal learning rate cannot be exactly calculated for a given data and employed model. The proper learning rate of the given model can be done through grid search of the approximated logarithmic scale within a set $\{0.1, 0.01, 10^{-3}, 10^{-4}, 10^{-5}\}$

[15]. Occasionally, the learning rate is obtained by performing a trial-and-error manner. To pick the optimal value of learning rate, this study conducts a sensitivity analysis of learning rate with the given values of {0.00001, 0.00003, 0.00005, 0.00007, 0.00009, ..., 0.9}. The learning rate that generates the highest accuracy will be selected to use in the final model.

5.5 Applicability of proposed methodology

The case study of shelter allocation in responding to flood in five districts of Surat Thani, Thailand including Muang, Phun Phin, Chaiya, Tha Chang, and Tha Chana. These five districts encompass 25 sub-districts cover 96 affected areas (neighborhoods), which consider as the economic center, transportation, and agricultural zones (Figure 5.4). These areas usually face floods during the rainy season. According to statistical data of great flood in 2011, there were 194,780 affected people scattering in 96 neighborhoods [53]. The average flood duration was estimated as six days.

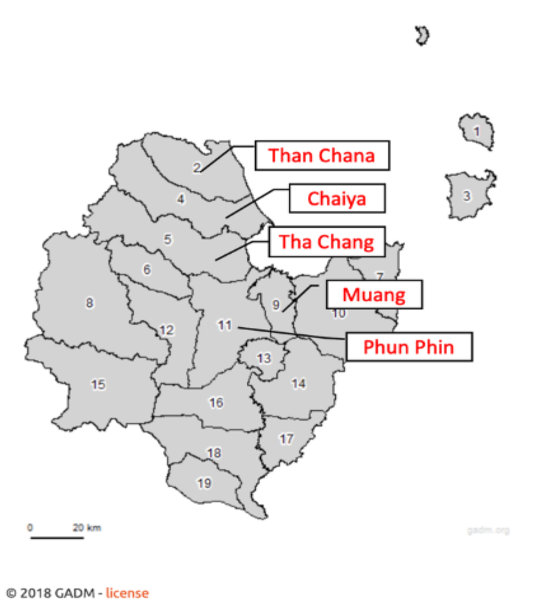


Figure 5.4: Case study areas

The Department of Disaster Prevention and Mitigation, Ministry of Interior of Thailand is the agency that takes responsibility for shelter location-allocation. The existing infrastructures are used as temporary shelters e.g. schools, city halls, temples, and gymnasiums. There were 84 candidate shelters and each shelter can accommodate 3,000 victims. During the onsets, government must pay for additional portable toilets and tents for locating kitchen, medical center, and warehouse for storing relief stuff. The cost of opening a shelter is approximately 144,000 THB. Moreover, the government also need to pay the staff wage for working in the shelter during the stays of victims. The ratio of required staff is one staff per 50 victims [14] and each is paid with a standard wage of 380 THB per day. The distance between the affected areas and candidate shelters are based on road networks which obtain from Google Maps Distance Matrix API. Based on decision-maker interview, the vehicles for evacuation belong to the Royal Thai Army which can handle 12 person per round as its capacity. The fuel consumption rate is 8 kilometers per liter. During the flood, the velocity of vehicle is estimated as 24 kilometers per hour [49]. The standard restriction time to evacuate victims from each area should not exceed 72 hours after the occurrence [17].

5.6 Experiment results

5.6.1 Results generated based on Epsilon Constraint method

First, each objective function is solved individually to define the upper and lower bound to use in solving multi-objective with epsilon constraint. The payoff table demonstrates the optimal solutions of f_1 and f_2 which minimize total cost, and total evacuation time of victims respectively (Table 5.1). It reveals that when seeking to minimize total cost, the total time of victims' evacuation is quite long because a small number of shelters are opened which leads to a longer time for transportation. On the other hand, when minimizing the total time for evacuation, several shelters are opened to shorten transportation time by ignoring to concern the total cost. The upper and lower bounds express in Table 5.1 are the epsilon constraint values (ϵ_{f_2}) that will be used for restricting the primary objective functions following equation (5.12).

After restricting the primary objective function with the epsilon value, the optimal solutions generated by epsilon constraint method are demonstrated in terms of selected shelters, total cost, and total evacuation time of all case study areas (Table 5.2).

The optimal solutions obtained from solving the proposed multi-objective optimization model by Epsilon Constraint are simulated to create the dataset. These simulated data are used as the input data of the ANN model. The simulated data indicate the shelter-allocation of all possible onset relying on the assumption that all affected would be attacked by disaster at a difference time. The data contain in table 5.3 are some part of the whole dataset. Herein, 0 means usual situation, 1 means flooding.

Table 5.1: Payoff table shows optimal solution obtained from individual solving f_1 and f_2

Area	Optimal solution f_1	Total time (Hours)	Optimal solution f_2	Total cost (THB)	Total Evacuation time (hour)	
					Lower bound	Upper bound
Muang-Watpradu	499,057	76.33	75.23	642,777	75.23	76.33
Muang-Khuntalae	821,768	104.13	107.49	823,198	104.13	107.49
Muang-Makhamtia	377,952	18.71	16.58	523,312	16.58	18.71
Muang-Klongchanak	258,831	17.88	17.88	258,831	17.88	17.88
Muang-Kongnoi	559,238	29.88	27.4	560,408	27.4	29.88
Muang-Bangsai	214,003	14.78	10.92	356,431	10.92	14.78
Phun Phin-Thakam	250,559	30.77	30.77	396,839	30.77	30.77
Phun Phin-Namrob	183,851	8.1	5.83	326,920	5.83	8.1
Phun Phin-Bang-ngon	214,547	11.12	10.7	504,637	10.7	11.12
Phun Phin-Leeled	227,671	26	21.51	372,180	21.51	26
Phun Phin-Malua	210,994	23.83	23.83	210,994	23.83	23.83
Chaiya-Pawae	369,403	19.35	19.35	369,403	19.35	19.35
Chaiya-Tung	336,305	6.37	6.07	482,450	6.07	6.37
Chaiya-Lamed	343,649	7.88	1.3	340,946	1.3	7.88
Chaiya-Wiang	342,649	5.46	5.46	342,649	5.46	5.46
Chaiya-Takrob	194,966	7.25	7.05	338,879	7.05	7.25
Chaiya-Pakmark	464,125	91.45	90.4	607,670	90.4	91.45
Tha Chang-Tha Chang	210,625	22.7	22.37	356,765	22.37	22.7
Tha Chang-Klonsai	206,050	11.73	10.56	349,555	10.56	11.73
Tha Chang-Thakhoei	216,639	20.91	20.91	216,639	20.91	20.91
Tha Chang-Parkchaluy	261,850	51.32	42.65	404,520	42.65	51.32
Tha Chang-Sawiat	585,940	56.58	60.85	774,883	56.58	60.85
Tha Chana- Tha Chana	558,900	125.48	126.43	758,038	125.48	126.43
Tha Chana-Wang	181,469	8.17	6.53	324,856	6.53	8.17
Tha Chana-Smorthong	181,534	8.89	5.73	468,347	5.73	8.89

Table 5.2: Shelter location-allocation based on epsilon constraint method

Area	Selected shelters	Total cost (THB)	Total evacuation time (hours)
Muang-Watpradu A1-A5	S2, S4	499,604	77.58
Muang-Khuntalae A6-A11	S6, S8, S10	823,198	107.49
Muang-Makhamtia A12-A14	S12, S14	377,952	18.71
Muang-Klongchanak A15-A18	S15	258,831	17.88
Muang-Kongnoi A19-A23	S20, S22	413,115	25.1
Muang-Bangsai A24-A26	S26	214,003	14.78
Phun Phin-Thakam A27-A29	S27	250,559	30.77
Phun Phin-Namrob A30-A32	S32	183,851	8.1
Phun Phin-Bang-ngon A33-A37	S33, S36	361,281	12.37
Phun Phin-Leeled	S37	227,671	26

Table 5.2: Shelter location-allocation based on epsilon constraint method

Area	Selected shelters	Total cost (THB)	Total evacuation time (hours)
A38-A40			
Phun Phin-Maluan A41-A43	S40	210,994	23.83
Chaiya-Pawae A44-A45	S44, S45	369,403	19.35
Chaiya-Tung A46-A48	S47, S48	336,305	6.37
Chaiya-Lamed A49-A51	S49, S50	343,649	7.88
Chaiya-Wiang A52-A54	S51, S53	342,649	5.46
Chaiya-Takrob A55-A57	S54	194,966	7.25
Chaiya-Pakmark A58-A62	S56, S58	459,559	85.92
Tha Chang A63-A65	S59	210,625	22.7
Tha Chang-Klonsai A66-A67	S62	206,050	11.73

Table 5.2: Shelter location-allocation based on epsilon constraint method

Area	Selected shelters	Total cost (THB)	Total evacuation time (hours)
Tha Chang-Thakhoei A68-A69	S65	216,639	20.91
Tha Chang-Parkchaluy A70-A72	S67, S68	404,520	42.65
Tha Chang-Sawiat A73-A80	S69, S71, S72, S73	585,698	56.18
Tha Chana A81-A89	S74, S75, S77, S78, S79	703,438	126.73
Tha Chana-Wang A90-A92	S80	181,469	8.17
Tha Chana-Smorthong A93-A96	S83	181,534	8.89

Table 5.3: Simulated data based on the optimal solution obtained from Epsilon Constraint method

Affected area																	Assigned Shelter
A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	...	A96	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	...	0	S4
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	...	0	S8
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	...	0	S8
0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	...	0	S8
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	...	0	S6
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	...	0	S6
0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	...	0	S6
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	...	0	S10
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	...	0	S10
0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	...	0	S10
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	...	0	S12
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	...	0	S14
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	S83

5.6.2 Shelter location-allocation based on ANN-EC

The simulated data are trained and tested with the ANN model under the different learning rates between 0.00001, 0.00003, 0.00005,..., 0.9. Since the solution approach has integrated the Epsilon Constraint method and ANN for determining shelter location-allocation, the proposed solution is called ANN-EC from now on. According to the optimal learning rate cannot be identified exactly, the sensitivity analysis is conducted to select the most proper learning rate of the model and given data (Table 5.4). With learning rate 0.1-0.9, the execution times are less than 1 minute but the accuracy performances are dramatically low. On the other hand, adjusting the learning rate with small values 0.007-0.00001 required a longer time for executions, but do not yield higher accuracy in anyway. Based on the given dataset, the sensitivity analysis exposes that the learning rates between 0.09-0.009 provide acceptable accuracy rate (above 70%), and learning rate 0.05 is the most appropriate value for using in the final model which generates the highest accuracy of 90.76% with the execution time 4.54 minutes (Figure 5.5).

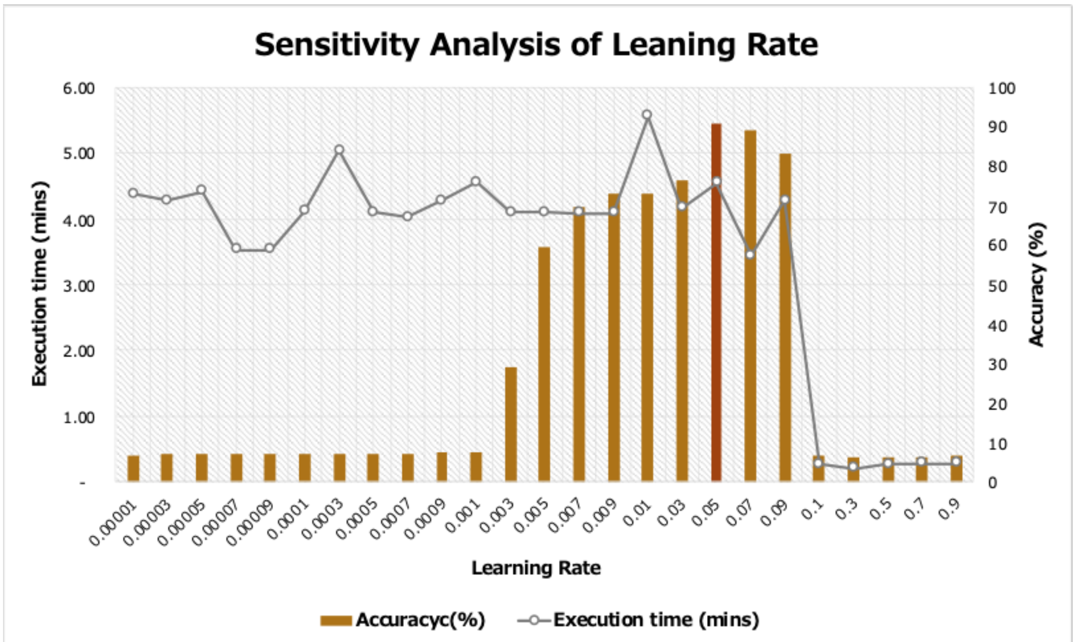


Figure 5.5: Sensitivity analysis of learning rates between 0.1-0.00001

Table 5.4: Accuracy and execution time varies on different learning rate

Learning Rate	Accuracy (%)	Execution time (mins)
0.00001	6.66	4.38
0.00003	7.18	4.27
0.00005	7.18	4.41
0.00007	7.18	3.53
0.00009	7.18	3.53
0.0001	7.18	4.11
0.0003	7.18	5.04
0.0005	7.18	4.1
0.0007	7.18	4.02
0.0009	7.71	4.28
0.001	7.71	4.55
0.003	29.21	4.1
0.005	59.53	4.1
0.007	69.76	4.09
0.009	72.84	4.08
0.01	72.84	5.55
0.03	76.39	4.16
0.05	90.76	4.54
0.07	89.21	3.44
0.09	83.24	4.27
0.1	6.66	0.27
0.3	6.16	0.2
0.5	6.16	0.27
0.7	6.16	0.28
0.9	6.68	0.28

Regarding the sensitivity analysis, the final ANN-EC model with a learning rate of 0.05 and momentum value 0.9 is employed to classify shelter location-allocation.

The results generated by Epsilon Constraint and ANN-EC are compared with the baseline i.e. current shelter location-allocation plan announced by the government sector and illustrated through comparisons graph (Figure 5.6). The blue dots and green dots are cost per person obtained from Epsilon Constraint and ANN-EC respectively. The blue line represents cost per person of the current shelter allocation plan. It was found that the results generated by ANN-EC are quite consistent with the optimal solutions produced by Epsilon Constraint method. Thus, it leads the green dots overlapped with blue dots. It can be stated that, solving the proposed model with both Epsilon Constraint and ANN-EC mainly provides better solutions than current plan determined by the government. The optimal solutions generated by Epsilon Constraint method outperform the current plan on the average of 67.11 %, while ANN-EC produces the better results than current plan on the average of 68.19 % (Table 5.5).

In aspect of evacuation time, the optimal solutions produced by the Epsilon Constraint method generated a greater evacuation time than current shelter location-allocation plan determined by the government. In the same way, the results produced by ANN-EC mostly worse than current shelter location-allocation plan (Figure 5.7). It was found that the optimal solutions produced by Epsilon Constraint method worse than current plant on the average of 20.77 %, and ANN-EC generated worse results than current plan around 98 % (Table 5.6). This is because the current shelter location-allocation plan is rather a decentralization. The victims from each area are assigned to served by different shelter that located nearby their house. As a result, the evacuation time is shorter, but an expensive cost requires to pay by the government sector.

Table 5.5: Comparisons of total cost per person generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Current VS EC	Current VS ANN-EC
A1	S1	4,769	S4	2,602	S4	2,717	2,167	2,052
A2	S3	664	S4	362	S4	378	302	286
A3	S2	832	S4	454	S4	474	378	358
A4	S5	3,236	S4	1,765	S4	1,843	1,470	1,392
A5	S4	1,047	S2	571	S49	596	476	450
A6	S7	756	S8	499	S53	540	257	216
A7	S10	1,084	S8	716	S8	774	368	310
A8	S8	1,689	S6	1,115	S6	1,207	574	483
A9	S6	623	S6	412	S6	445	212	178
A10	S9	1,131	S10	747	S10	808	384	323
A11	S11	1,446	S10	955	S10	1,033	491	413
A12	S14	1,137	S14	822	S14	822	315	315
A13	S12	870	S12	629	S12	629	241	241
A14	S13	783	S14	566	S14	566	217	217
A15	S15	467	S15	301	S15	301	166	166
A16	S16	772	S15	498	S15	498	274	274
A17	S16	1,481	S15	955	S15	955	525	525
A18	S15	585	S15	377	S15	377	208	208
A19	S17	1,575	S20	771	S20	771	804	804

Table 5.5: Comparisons of total cost per person generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Current VS EC	Current VS ANN-EC
A20	S18	1,180	S20	578	S20	578	603	603
A21	S23	2,411	S22	1,180	S22	1,180	1,231	1,231
A22	S20	2,461	S22	1,204	S22	1,204	1,256	1,256
A23	S19	1,592	S20	779	S20	779	813	813
A24	S25	1,035	S26	443	S26	443	592	592
A25	S26	2,242	S26	960	S26	960	1,282	1,282
A26	S24	775	S26	332	S26	332	443	443
A27	S27	1,520	S27	696	S27	696	824	824
A28	S28	759	S27	348	S27	348	411	411
A29	S29	568	S27	260	S27	260	308	308
A30	S30	2,038	S32	792	S32	792	1,246	1,246
A31	S31	1,403	S32	546	S32	546	858	858
A32	S32	2,296	S32	892	S32	892	1,403	1,403
A33	S35	2,000	S36	1,112	S36	1,132	889	868
A34	S34	2,097	S36	1,165	S36	1,187	932	910
A35	S36	2,032	S36	1,129	S36	1,150	903	882
A36	S33	2,827	S33	1,571	S67	1,600	1,256	1,227
A37	S36	2,611	S36	1,451	S36	1,478	1,160	1,133
A38	S39	641	S37	285	S37	285	356	356

Table 5.5: Comparisons of total cost per person generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Current VS EC	Current VS ANN-EC
A39	S37	1,190	S37	529	S37	529	661	661
A40	S38	1,391	S37	619	S37	619	772	772
A41	S40	896	S40	375	S40	375	521	521
A42	S41	1,105	S40	463	S40	463	642	642
A43	S42	2,376	S40	995	S40	995	1,381	1,381
A44	S44	438	S45	438	S6	493	-	(55)
A45	S45	515	S44	515	S53	580	-	(65)
A46	S46	854	S48	597	S65	597	256	256
A47	S47	3,141	S47	2,198	S47	2,198	943	943
A48	S48	2,011	S47	1,407	S47	1,407	604	603
A49	S49	1,164	S50	1,173	S6	1,256	(9)	(93)
A50	S50	1,096	S49	1,105	S49	1,184	(9)	(87)
A51	S50	692	S49	697	S67	747	(5)	(55)
A52	S51	1,320	S53	931	S53	1,018	389	302
A53	S52	1,974	S53	1,393	S8	1,522	581	452
A54	S53	1,018	S51	718	S6	785	300	233
A55	S55	722	S54	416	S54	416	306	306
A56	S54	1,605	S54	924	S54	924	681	681
A57	S55	1,052	S54	605	S54	605	446	446

Table 5.5: Comparisons of total cost per person generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Current VS EC	Current VS ANN-EC
A58	S56	1,413	S56	1,094	S56	1,094	319	319
A59	S58	1,058	S58	819	S58	819	239	239
A60	S57	1,141	S58	884	S58	884	257	257
A61	S58	1,285	S56	995	S56	995	290	290
A62	S58	618	S58	478	S58	478	139	139
A63	S59	898	S59	374	S59	374	524	524
A64	S60	4,211	S59	1,755	S59	1,755	2,456	2,456
A65	S61	898	S59	374	S59	374	524	524
A66	S62	431	S62	254	S62	254	177	177
A67	S63	883	S62	520	S62	520	362	362
A68	S64	593	S65	355	S65	355	239	239
A69	S65	460	S65	275	S65	275	185	185
A70	S66	849	S67	620	S67	636	229	213
A71	S67	767	S68	560	S53	575	207	192
A72	S68	792	S67	579	S67	594	214	199
A73	S69	2,253	S72	1,830	S71	1,867	423	386
A74	S70	729	S71	592	S71	604	137	125
A75	S70	2,218	S71	1,802	S71	1,838	416	381
A76	S71	2,212	S73	1,797	S73	1,832	415	379

Table 5.5: Comparisons of total cost per person generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Current VS EC	Current VS ANN-EC
A77	S72	889	S72	722	S72	737	167	152
A78	S69	2,212	S69	1,797	S53	1,832	415	379
A79	S69	2,318	S71	1,883	S71	1,921	435	398
A80	S73	2,461	S73	1,999	S8	2,039	462	422
A81	S75	1,139	S75	1,421	S75	1,416	(282)	(277)
A82	S78	2,097	S74	2,615	S65	2,606	(519)	(510)
A83	S74	1,880	S77	2,345	S77	2,337	(465)	(457)
A84	S74	2,256	S79	2,814	S79	2,804	(558)	(548)
A85	S74	1,925	S75	2,401	S75	2,393	(476)	(468)
A86	S77	1,762	S78	2,198	S78	2,191	(436)	(428)
A87	S76	2,892	S77	3,607	S77	3,595	(715)	(703)
A88	S78	2,820	S77	3,517	S77	3,505	(697)	(686)
A89	S79	1,104	S75	1,377	S75	1,372	(273)	(268)
A90	S80	1,622	S80	907	S80	907	715	715
A91	S81	927	S80	518	S80	518	408	408
A92	S81	1,622	S80	907	S80	907	715	715
A93	S82	2,351	S83	908	S83	908	1,443	1,443
A94	S82	2,351	S84	908	S84	908	1,443	1,443
A95	S82	3,135	S85	1,210	S85	1,210	1,924	1,924

Table 5.5: Comparisons of total cost per person generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Assigned shelter	Cost (THB/person)	Current VS EC	Current VS ANN-EC
A96	S82	2,351	S86	908	S86	908	1,443	1,443
Average Improvement (Percentage)							67.11	68.19

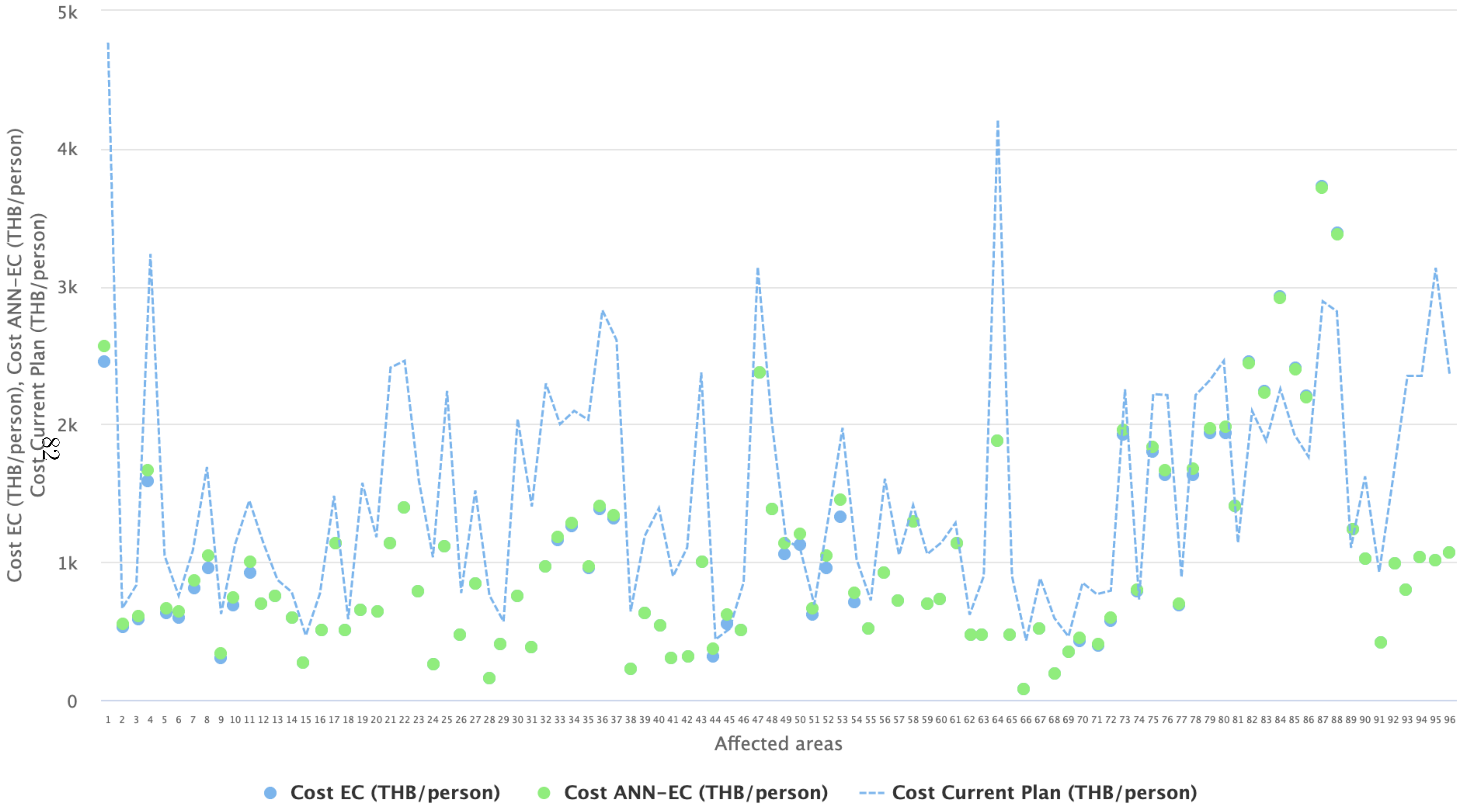


Figure 5.6: Comparisons of total cost per person generated by EC,ANN-EC, and current shelter location-allocation

Table 5.6: Comparisons of evacuation time generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Current VS EC	Current VS ANN-EC
A1	S1	1.87	S4	4.47	S4	4.47	(3)	(3)
A2	S3	18.98	S4	25.68	S4	25.68	(7)	(7)
A3	S2	1.58	S4	23.59	S4	23.59	(22)	(22)
A4	S5	2.33	S4	5.58	S4	5.58	(3)	(3)
A5	S4	16.00	S2	18.25	S49	68.75	(2)	(53)
A6	S7	11.43	S8	27.53	S53	179.67	(16)	(168)
A7	S10	16.33	S8	16.83	S8	16.83	(1)	(1)
A8	S8	12.02	S6	12.78	S6	12.78	(1)	(1)
A9	S6	29.75	S6	29.75	S6	29.75	-	-
A10	S9	5.86	S10	11.72	S10	11.72	(6)	(6)
A11	S11	7.38	S10	8.88	S10	8.88	(2)	(2)
A12	S14	7.73	S14	7.73	S14	7.73	-	-
A13	S12	5.77	S12	5.77	S12	5.77	-	-
A14	S13	1.80	S14	5.20	S14	5.20	(3)	(3)
A15	S15	7.00	S15	7.00	S15	7.00	-	-
A16	S16	1.13	S15	4.20	S15	4.20	(3)	(3)
A17	S16	0.42	S15	1.08	S15	1.08	(1)	(1)
A18	S15	5.60	S15	5.60	S15	5.60	-	-
A19	S17	0.83	S20	4.80	S20	4.80	(4)	(4)

Table 5.6: Comparisons of evacuation time generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Current VS EC	Current VS ANN-EC
A20	S18	2.30	S20	9.70	S20	9.70	(7)	(7)
A21	S23	4.85	S22	3.35	S22	3.35	1	1
A22	S20	1.85	S22	2.45	S22	2.45	(1)	(1)
A23	S19	7.65	S20	4.80	S20	4.80	3	3
A24	S25	5.03	S26	7.65	S26	7.65	(3)	(3)
A25	S26	2.27	S26	2.27	S26	2.27	-	-
A26	S24	2.48	S26	4.86	S26	4.86	(2)	(2)
A27	S27	3.50	S27	3.50	S27	3.50	-	-
A28	S28	8.99	S27	8.99	S27	8.99	-	-
A29	S29	27.63	S27	18.28	S27	18.28	9	9
A30	S30	1.47	S32	2.60	S32	2.60	(1)	(1)
A31	S31	1.60	S32	3.30	S32	3.30	(2)	(2)
A32	S32	2.20	S32	2.20	S32	2.20	-	-
A33	S35	0.30	S36	2.35	S36	2.35	(2)	(2)
A34	S34	2.60	S36	4.10	S36	4.10	(1)	(1)
A35	S36	2.70	S36	2.70	S36	2.70	-	-
A36	S33	0.97	S33	0.97	S67	16.67	-	(16)
A37	S36	2.25	S36	2.25	S36	2.25	-	-
A38	S39	3.03	S37	12.02	S37	12.02	(9)	(9)

Table 5.6: Comparisons of evacuation time generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Current VS EC	Current VS ANN-EC
A39	S37	6.87	S37	6.87	S37	6.87	-	-
A40	S38	1.11	S37	7.12	S37	7.12	(6)	(6)
A41	S40	10.83	S40	10.83	S40	10.83	-	-
A42	S41	8.87	S40	8.67	S40	8.67	0	0
A43	S42	4.43	S40	4.33	S40	4.33	0	0
A44	S44	8.75	S45	8.75	S6	110.00	-	(101)
A45	S45	10.60	S44	10.60	S53	19.00	-	(8)
A46	S46	0.92	S48	4.08	S65	4.17	(3)	(3)
A47	S47	0.65	S47	0.65	S47	0.65	-	-
A48	S48	0.06	S47	1.63	S47	1.63	(2)	(2)
A49	S49	0.00	S50	1.25	S6	25.42	(1)	(25)
A50	S50	1.30	S49	2.80	S49	2.80	(1)	(1)
A51	S50	0.00	S49	3.82	S67	37.50	(4)	(37)
A52	S51	1.34	S53	2.16	S53	2.16	(1)	(1)
A53	S52	1.58	S53	1.50	S8	25.42	0	(24)
A54	S53	0.19	S51	1.80	S6	53.33	(2)	(53)
A55	S55	4.40	S54	4.60	S54	4.60	(0)	(0)
A56	S54	0.40	S54	0.40	S54	0.40	-	-
A57	S55	1.55	S54	2.25	S54	2.25	(1)	(1)

Table 5.6: Comparisons of evacuation time generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Current VS EC	Current VS ANN-EC
A58	S56	14.12	S56	14.12	S56	14.12	-	-
A59	S58	9.92	S58	9.92	S58	9.92	-	-
A60	S57	0.75	S58	14.48	S58	14.48	(14)	(14)
A61	S58	0.67	S56	15.53	S56	15.53	(15)	(15)
A62	S58	31.88	S58	31.88	S58	31.88	-	-
A63	S59	12.58	S59	12.58	S59	12.58	-	-
A64	S60	1.53	S59	1.45	S59	1.45	0	0
A65	S61	13.75	S59	8.67	S59	8.67	5	5
A66	S62	7.35	S62	7.35	S62	7.35	-	-
A67	S63	3.21	S62	4.38	S62	4.38	(1)	(1)
A68	S64	5.50	S65	6.33	S65	6.33	(1)	(1)
A69	S65	14.58	S65	14.58	S65	14.58	-	-
A70	S66	4.58	S67	11.73	S67	11.73	(7)	(7)
A71	S67	20.58	S68	11.92	S53	36.83	9	(16)
A72	S68	30.00	S67	19.00	S67	19.00	11	11
A73	S69	1.90	S72	2.50	S71	5.15	(1)	(3)
A74	S70	0.00	S71	14.59	S71	14.59	(15)	(15)
A75	S70	0.00	S71	5.15	S71	5.15	(5)	(5)
A76	S71	5.15	S73	6.35	S73	6.35	(1)	(1)

Table 5.6: Comparisons of evacuation time generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Current VS EC	Current VS ANN-EC
A77	S72	17.85	S72	17.85	S72	17.85	-	-
A78	S69	2.50	S69	2.50	S53	6.40	-	(4)
A79	S69	0.50	S71	5.15	S71	5.15	(5)	(5)
A80	S73	2.08	S73	2.08	S8	22.50	-	(20)
A81	S75	29.33	S75	29.33	S75	29.33	-	-
A82	S78	27.25	S74	25.46	S65	19.58	2	8
A83	S74	2.17	S77	3.50	S77	3.50	(1)	(1)
A84	S74	19.50	S79	16.13	S79	16.13	3	3
A85	S74	17.79	S75	16.29	S75	16.29	2	2
A86	S77	4.20	S78	2.90	S78	2.90	1	1
A87	S76	1.03	S77	2.77	S77	2.77	(2)	(2)
A88	S78	1.03	S77	1.03	S77	1.03	-	-
A89	S79	35.40	S75	29.33	S75	29.33	6	6
A90	S80	3.80	S80	3.80	S80	3.80	-	-
A91	S81	0.10	S80	3.30	S80	3.30	(3)	(3)
A92	S81	1.90	S80	1.07	S80	1.07	1	1
A93	S82	4.13	S83	3.03	S83	3.03	1	1
A94	S82	1.47	S84	3.30	S84	3.30	(2)	(2)
A95	S82	0.93	S85	0.93	S85	0.93	-	-

Table 5.6: Comparisons of evacuation time generated by EC, ANN-EC, and current shelter location-allocation

Affected areas	Current Shelter Allocation		EC		ANN		Differentiation	
	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Assigned shelter	Time (Hours)	Current VS EC	Current VS ANN-EC
A96	S82	4.10	S86	1.63	S86	1.63	2	2
Average Improvement (Percentage)							(20.77)	(98.06)

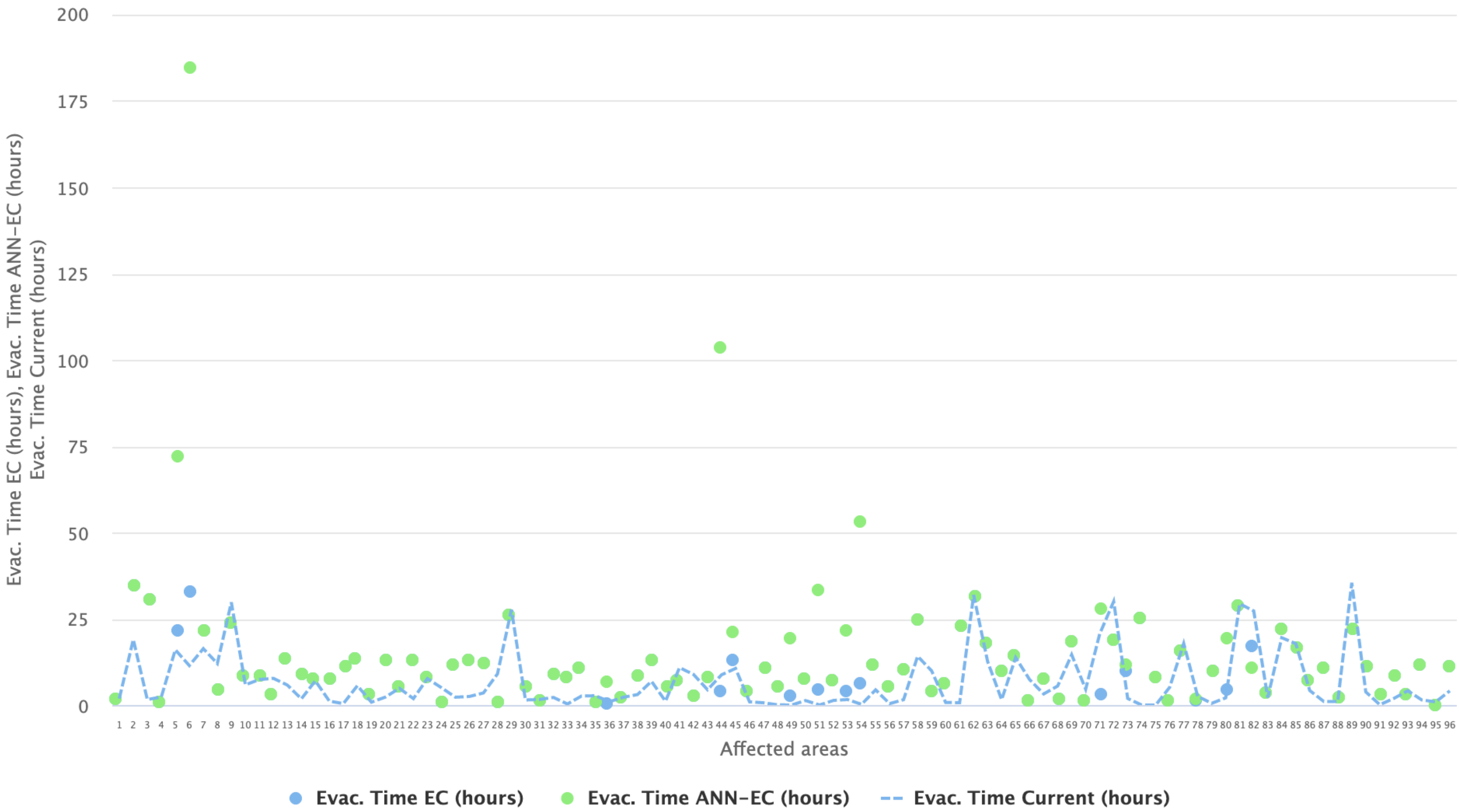


Figure 5.7: Comparisons of evacuation time generated by EC, ANN-EC, and current shelter location-allocation

5.7 Conclusion

This study involves determining shelter location-allocation in responding to humanitarian logistics. The first step begins with proposing a multi-objective optimization model which aims at minimizing the total cost and minimizing the total time for victims' evacuation. The Epsilon Constraint approach is used to deal with these conflicting objectives. The optimal solutions illustrate the selected shelters to serve the victims in each area. It reveals that one shelter can accommodate the victims from several affected areas regarding the assumption of the model. However, the onsets would not occur concurrently in a real situation such as previously two affected areas ever confronted disaster at the same time and assigned to share the same shelter, but in the future either one area supposes to face disaster again, but another is safe, then it is arguable whether the shelter allocation plan would be the same. The probability of disaster onsets would arise in numerous patterns and tends to be more complex when conduct decision-making for several areas. Therefore, this study employs ANN to deal with large scale data for dealing with this complexity. In this matter, the obtained optimal solutions are simulated to express possible situations that would arise in all affected areas together with assigned shelters. The datasets are test and train by ANN. The sensitivity analysis is performed to define the optimal learning rate that can generate the best accuracy rate. Applicability of the proposed methodology is demonstrated through the case study of shelter location-allocation for flood areas of five districts encompass 96 affected areas (neighborhoods) of Surat Thani, Thailand. The final ANN model is used to train and test these data with the optimal learning rate of 0.05 and a momentum of 0.9. The shelter allocation results generated by both Epsilon Constraint method and ANN are shown and compared. The results obtained from ANN quite a consistency with epsilon constraint method both in aspects of total cost per person and total evacuation time. However, it was found that ANN outperforms the optimization-based method in some cases.

In conclusion, it can be stated that the dataset for using as the input of ANN are acquired from solving multi-objective optimization problem with epsilon constraint method. Combining two methods for determining shelter location-allocation is the contribution of this study. To the best of our knowledge, there are no prior works proposed this methodology, especially in the context of humanitarian logistics. Nevertheless, this study still has some limitations due to the simulated dataset obtained from optimization-based method in which tested with specific affected areas. It may not compatible with other case studies that have different characteristics. Yet, it would be advantageous for decision-makers of these 96 areas when they make decisions on shelter allocation in the future.

Chapter 6

Two-stage Facilities Location-allocation Model in Responding to Relief Supply Chain

6.1 Introduction

The occurrences of natural catastrophes have caused noteworthy damages to humankind, social, and economic sectors. In 2019, there were globally 396 disasters attacking reported. The effects of disasters resulted in 11,755 dead, 95 million people affected, and $103 billion economic losses. Among all occurrences, flood was one of the most frequent catastrophes which radically impacted the highest number of affected people around the world, especially in Asia [11].

Manipulating the proper logistics practices to simplify disaster management is recognized as the *"humanitarian logistics"*. The goal of humanitarian logistics is to alleviate the victims' suffers through the processes of rescuing the victims from disrupted area to safe zones, as well as planning, storing, and delivery the relief supplies such as temporary shelters, foods, potable water, survival bags, medical supplies, tents, generators, etc. [58, 59] for healing efforts with the right time, right quantity to the right place [34, 54]. Furthermore, humanitarian logistics and humanitarian supply chain beyond focuses on the relationship among the related parties to facilitate such mobilizing possible which is very important to respond to the catastrophes properly [56].

Humanitarian logistics and supply chain also relates decision-making on facilities location-allocation, e.g. shelter, distribution center, warehouse, or healthcare center is very vital since it takes a long-time effect, requires a considerable investment, and involves many parties [47, 48]. Among all facilities, finding temporary shelters to support the victims is an important issue that must be considered beforehand [47]. Moreover, a proper manner for justifying facility location-allocation helps decision-makers to avoid ad-hoc decision making. In this case, optimization techniques are employed for efficient allocating scarce resources which impact the success of humanitarian supply chain best practices [57].

To entirely improve both effective and efficient criteria along the supply chain, developing multi-echelon facility location-allocation model is essential. Regarding a literature survey in Chapter 2, majority of previous studies usually present the single echelon for relief facility location-allocation. There is only relative small number of studies that develop the several echelon. Moreover, when determining the objective functions of the multi-echelon facility location-allocation models, majority of the studies generally proposed the single objective optimization models for location-allocation. The limitation of a single objective function could ignore some important criteria. Therefore, it is necessity to consider various echelon facility location-allocation for improving the whole supply chain, and should take into account the considerable criteria concurrently for achieving the desired goals of the humanitarian relief supply chain.

This study proposes a multi-objective optimization model for two-echelon or two-stage facilities location-allocation. The first echelon is focused on the process of evacuating the victims from the disrupted areas to the selected shelters. Both efficiency and effectiveness are taken into account for determining shelter site selection and allocation. Therein, the efficient shelter site selection-allocation model proposed by [48] is employed and extended by including a further considerable criterion, i.e. the total time for victims' evacuation. For the second echelon, it involves justifying the suitable locations to utilized as the distribution centers for storing and distributing the relief supplies to serve the victims who stay in the selected shelters. Mathematical model is formulated to minimize the total transportation cost between the candidate distribution centers and the open shelters. The application of the proposed model is illustrated through the flood case study in Tha Uthae, Surat Thani of Thailand.

The originality of this study mainly relates the model formulation that concurrently considering both efficient and effective criteria in which the prior work mostly ignored determining simultaneously. Furthermore, the proposed model seeks to improve two echelons, i.e. preparedness phase and response phase. The powerful solution approach Epsilon Constraint is employed for dealing with the multi-objective optimization problem to avoid assigning weight coefficient to the incomparable objective function and avoiding defined the preference values that lead to face with ambiguity in which the prior work did not consider this matter.

6.2 Proposed methodology

The mathematical formulation for the two-echelon facilities location-allocation model is proposed. The first echelon attempts to define proper shelter location-allocation and the second echelon aims to assign the appropriate distribution centers to store and dispatch the relief supplies to the open shelters. The relationship and linkages between two echelon is demonstrated in the Figure 6.1. The assumptions of two-echelon relief facility location-allocation model can be described as follows:

Assumptions

- The number of victims in each affected area is known and fixed

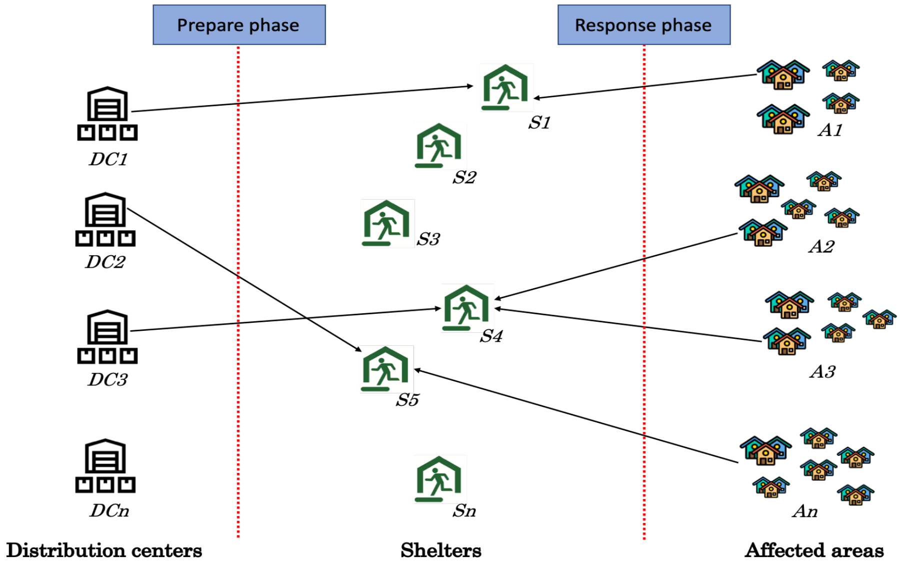


Figure 6.1: Design of two echelon relief facility location-allocation

- The locations of all affected areas, candidate shelters, and candidate distribution center are fixed
- The victims in each affected area are evacuated to the selected shelters as the entire unit and not permit to separately assign to different shelters
- The vehicles using in evacuation process and relief supplies distribution are homogeneous
- The velocity of the vehicles is constant, the traffic conditions are ignored to consider

Model formulation

1) First echelon model

The first echelon involves a disaster response phase which aims at evacuating the victims from the affected areas and seeking the appropriate shelters to serve the victims. Herein, a set of candidate shelters is predetermined. The existing infrastructures such as schools, temples, municipalities are used as the candidate shelters. To improve both effective and efficient criteria together, the multi-objectives function is formulated to 1) minimize the total cost which combines fixed cost for opening shelters, victims' transportation cost, and service cost, and 2) minimize the total time for victims' evacuation. The mathematical model, indices, parameters, and decision variables are illustrated as follows:

Indices

I	Set of affected areas
J	Set of candidate shelters

Parameters

d_{ij}	Distance between affected area i and candidate shelter j
h_i	Number of victims in area i
f_j	Fixed cost for opening the shelter j
Cap_j	Capacity of the candidate shelter j
Cap_v	Capacity of vehicle
m_{ij}	Maximum acceptable distance between area i and shelter j
N	Number of vehicles for evacuation process
T	Duration of the disaster occurrence
V	Velocity of the vehicle using in evacuation process
W	Time for evacuating the victims in area i to shelter j
α	Constant coefficient of transportation cost per kilometer per person
β	Wage per person for hiring staff to work in the shelter
γ	Ratio of the required staff per victim

Decision variables

X_j	1, if candidate shelter j is selected or otherwise 0
Y_{ij}	1, if affected area i is assigned to shelter j or otherwise 0
P_{ij}	Number of victims in area i that are assigned to shelter j

Objective functions

$$Min \quad f_1 = \sum_{j \in J} X_j f_j + \alpha \sum_{i \in I} \sum_{j \in J} d_{ij} Y_{ij} h_i + \beta T \sum_{i \in I} \frac{P_{ij}}{\gamma} \tag{6.1}$$

To develop the model, a set of the affected areas I and a set of predetermined shelters J are incorporated. The first objective function (6.1) of the proposed model aims to minimize the total cost which includes three terms i.e. fixed cost for opening shelters, victim's transportation cost, and victim service cost.

$$Min \quad f_2 = \sum_{i \in I} \sum_{j \in J} \frac{d_{ij} Y_{ij}}{V} \cdot \frac{h_i}{NCap_v} \tag{6.2}$$

The second objective function (6.2) aims at minimizing the total time for victim's evacuation. In this case, the data including distance between affected area i to shelter j, number of victims that are mobilized, number and capacity of vehicles, and vehicle's speed during the flood are determined. The constraints for the objectives functions can be defined as Equation (6.3)-(6.10).

Subject to

$$\sum_{j \in J} Y_{ij} = \quad 1, \quad \forall_{i \in I} \tag{6.3}$$

Constraint (6.3) limits an affected area i must be entirely assigned to only single shelter j and must not be separately assigned to different shelters

$$Y_{ij} \quad \leq \quad X_j, \quad \forall_{i \in I, j \in J} \tag{6.4}$$

Constraint (6.4) restricts an affected area i must be assigned to only open shelter j.

$$d_{ij}Y_{ij} \quad \leq \quad m_{ij}, \quad \forall_{i \in I, j \in J} \tag{6.5}$$

Constraint (6.5) restrains the distance between an affected area i to assigned shelter j must not greater than a maximum acceptable distance.

$$\frac{d_{ij}Y_{ij}}{V} \cdot \frac{h_i}{NCap_v} \leq W, \quad \forall_{i \in I, j \in J} \tag{6.6}$$

Constraint (6.6) confines the duration for evacuating the victims from an affected area i to selected shelter j not longer than a particular restrict time W (hours).

$$\sum_{i \in I} P_{ij} \quad \leq \quad Cap_j X_j, \quad \forall_{j \in J} \tag{6.7}$$

Constraint (6.7) restricts the number of victims from each area i must not exceed capacity of selected shelter j.

$$\sum_{j \in J} P_{ij} = h_i, \quad \forall_{i \in I} \tag{6.8}$$

Constraint (6.8) restrains the number of assigned victims equal to the number of victims in each affected area i.

$$X_j \in \{0, 1\}, \quad \forall_{j \in J} \tag{6.9}$$

Constraint (6.9) defines the binary variable, X_j is 1 if candidate shelter is selected to open, otherwise 0.

$$Y_{ij} \in \{0, 1\}, \quad \forall_{i \in I, j \in J} \tag{6.10}$$

Constraint (6.10) defines the binary variable, Y_{ij} is 1 if affected area i is allocated to candidate shelter j, otherwise 0.

Since the proposed model attempts to improve the performance of humanitarian logistics in the practical manner, there are two criteria of cost and time that taken into account when formulating mathematical model for location-allocation. Solving a multi-objective optimization is more complex than solving a single objective model that the solution can be obtained straightforwardly. In this circumstance, the multi-objective optimization model is denoted as Equation (6.11)-(6.12). Where $x = x_1, x_2, ..., x_n$ is the vector of decision variables, and S is a set of feasible solutions.

$$Max \ or \ Min \qquad f(x) = (f_1(x), f_2(x)) \tag{6.11}$$

Subject to

$$x \in S \tag{6.12}$$

Regarding the above equations, the set of feasible solutions is recognized as a Pareto optimal set which is compromising among various objectives. There is no single optimal solution that can optimize all objective functions at the same time. To avoid the vague causes by predetermining the preference value and assigning the weight to incomparable criteria, this study selects the Epsilon Constraint method for dealing with multi-objective optimization model for relief facility location-allocation problem. With this method, only one objective function is chosen as the primary objective while other objectives are transformed to be the constraints of primary objective function. However, the right-hand side values of the transformed constraints should be known. Therefore, it is necessity to solve the inferior objective function individually to obtain the optimal solutions for assigning as the ϵ_2,ϵ_3,...ϵ_p, where p is the number of objective functions.

According to the prior works, the characteristics of disaster and relief requirements are determined for solving the social issues and enhance the performance of relief supply chain in terms of efficiency and effectiveness. Yet, a large number of the previous works focused on improving a specific echelon instead of several echelons which still be the limitation for improving the whole relief supply chain. In aspect of model formulation, the research works were extensively proposed as single-objective optimization which attempts to improve either efficiency or effectiveness. There are a relatively small number of studies that considered several objective functions concurrently. Nevertheless, the considered criteria emphasize improving either effectiveness or efficiency such as [16], and [10] that proposed the model to improve effectiveness but ignore the efficiency. For solution methods, the well-known approaches e.g. Weighted Goal Programming, and Weighted Sum Method usually employed by the researchers to deal with several objective functions. Nevertheless, these methods may not appropriate for dealing with multi-objective optimization for location-allocation in the context of humanitarian logistics as previously illustrated in the literature review part. This study aims to improve the research gaps by considering both criteria simultaneously and use the more proper solution i.e. Epsilon Constraint method to deal with the multi-objective optimization problem for facility location-allocation with two-echelon for improving the relief supply chain.

In this study, the first objective function (6.1) which seeks to minimize the total cost is selected to be the primary objective function, while the second objective function (6.2) is transformed to the constraint of the primary objective since cost efficiency is an important criterion that reflects how well of resource utilization which could be limited during disaster attacking period. Furthermore, decision-makers can plan and adequately allocate the budget for preparing and responding to catastrophes by determining the cost criterion. Without an appropriate for determining cost, it could affect the victims' welfare. Therefore, solving the bi-objective optimization for facility location-allocation by using Epsilon Constraint method can be illustrated as follows:

Objective function

$$Min \quad f_1(x) \tag{6.13}$$

Subject to

$$f_2(x) \leq \epsilon_2 \tag{6.14}$$

(6.3) - (6.10)

2) Second echelon model

The second echelon a preparedness phase that aims to select appropriate distribution centers for storing and distributing the emergency supplies kits to the victims who reside in the open shelters. The district office, municipality, or sub-district administration organization are used as the potential distribution centers. The objective function is formulated to minimize the transportation cost between the selected distribution centers and the selected shelters which acquired from solving the model in the first echelon. The model, indices, parameters and decisions variable can be formulated as follows:

Indices

K	Set of open shelters
L	Set of candidate distribution centers

Parameters

d_{kl}	Distance between open shelter k and distribution center l
m_{kl}	Maximum acceptable distance between open shelter k and distribution center l
s_k	Number of open shelters k
ζ	Constant coefficient of transportation cost per kilometer per round
Cap_l	Capacity of distribution center l

Decision variable

Z_{kl}	1, if shelter k is served by distribution center l or otherwise 0

Objective function

$$Min \quad f_3 = \zeta \sum_{k \in K} \sum_{l \in L} d_{kl} z_{kl} T \tag{6.15}$$

The objective function is to minimize the total transportation cost between distribution centers and open shelters. Therein, the transportation cost is estimated regarding the distance between distribution centers and shelters together with the frequency of trips which determines based on duration of disaster occurrence.

Subject to

$$d_{kl}Z_{kl} \quad \leq \quad m_{kl}, \quad \forall_{k\in K, l\in L} \tag{6.16}$$

Constraint (6.16) restrict the transportation distance between open shelter k and selected distribution center l is not farther maximum acceptable distance m_{kl}.

$$\sum_{k\in K} s_k \quad \leq \quad Cap_l Z_{kl}, \quad \forall_{l\in L} \tag{6.17}$$

Constraint (6.17) limits total the number of open shelters should not over the capacity of selected distribution centers.

$$Z_{kl} \quad \in \{0,1\}, \quad \forall_{k\in K, l\in L} \tag{6.18}$$

Constraint (6.18) defines the binary variable, Z_{kl} is 1 if candidate distribution center is decided to open, otherwise 0.

The numerical experiment is conducted by using the What'sBest LINDO Optimization with laptop Microsoft Windows 10, Intel(R) Core (TM) 1.51

GHz, RAM 4.0 GB. The proposed model is tested with the flood case study which is demonstrated in the next section.

6.3 Applicability of the proposed model

The real-world case of the great flood in Tha Uthae, Surat Thani province of Thailand is used to test the proposed model of the study. The terrain of Tha Uthae is a lowland and usually faces with flooding, especially during the rainy season. Based on the great flood of Tha Uthae in 2011, Surat Thani National Statistical Office reported that, there were 10 affected areas, 20 candidate shelters and 5,076 victims that suffered from the submerged [53].

Table 6.1: Affected area and number of victims

Area	No. of victims (person)	Area	No. of victims (person)
A1	750	A6	250
A2	540	A7	350
A3	400	A8	450
A4	800	A9	500
A5	650	A10	386

The related authorities involve the relief process by evacuating the victims from the affected areas to the temporary shelters. The Department of Disaster Prevention and Mitigation, Ministry of Interior of Thailand is the agency that takes the responsibility in shelter site selection and allocation. Although there is no construction cost since existing infrastructures are utilized as shelters, some fixed cost still exist due to the installation of portable toilets, and tents for using as temporary kitchen, medical center, and warehouse. Therefore, the cost for opening a shelter is estimated as 144,000 THB per shelter.

Since the position of both affected areas and candidate shelters are known, the distance based on road network is acquired from the Google Maps Distance Matrix API. The vehicles that are used in victims evacuation process belong to the Royal Thai Army. There are 3 vehicles available in each selected shelter. The vehicle's capacity is 12 persons, a fuel consumption rate is 8 kilometers per liter, and vehicle's speed during the inundation is 24 kilometers per hour based on the estimated function of flood depth and vehicle's speed proposed by [49].

The authorities require to pay the service cost which arise when serving the victims during the time they residing in the shelters. In this case, a service cost is determined regarding a cost of staff hiring. The government staffs are paid by their agencies with the standard wage of 380 THB per person per day. The number of required staff is 1 staff per 50 victims [14]. An average duration of the disaster occurrence based on the historical data is 6 days. Therefore, the service cost is estimated the whole cost for hiring the staff during 6 days.

For distribution centers, the district office, municipality, or sub-district administration organization are utilized as the candidate distribution centers. Each distribution center can serve the open shelters not exceed three shelters. The trucks will transport the relief supplies from the selected distribution center to open shelter once a day. According to the location of open shelters and candidate distribution centers are known, the road network distance also can obtain from the Google Maps Distance Matrix API. The maximum acceptable distance between open shelter and distribution center must not longer than 50 kilometers.

6.4 Numerical experiment results

The numerical experiment begins with solving the first echelon model which involves defining locations of shelters and assigning the selected shelters to the affected areas. The selected shelters are latterly used for determining the location-allocation of the distribution centers in the second echelon. The experiment results of each echelon are demonstrated as follows:

6.4.1 Numerical experiment results of the first echelon

In the first echelon, there are two objective functions that incorporated for determining an appropriate shelter location-allocation. The Epsilon Constraint is employed to solve the multi-objective optimization problem for shelter location-allocation. Therein, the first objective function (6.1) which seeks to minimize total cost is selected to be the primary objective (6.13), while another objective function (6.2) that aims to minimize total time for victims evacuation is transformed to be the constraint (6.14) for restricting the primary objective function.

Initially, the objective function (6.2) is individually solved in order to define the optimal solution of total time for evacuated the victims in all affected areas to the selected shelters. The result indicates that, the optimal solution of total time for evacuated the victims in all affected areas to the selected shelters is 367.58 hours. There are 3 shelters required to open for serving the victims, the total cost is 760,146 THB. The shelters location-allocation can be illustrated in Table 6.2.

Table 6.2: Shelter location-allocation generated by solving the second objective function

Open shelters	Shelter location-allocation
S18	A1, A4,
S19	A2, A5, A9
S20	A3, A6, A7, A8, A10

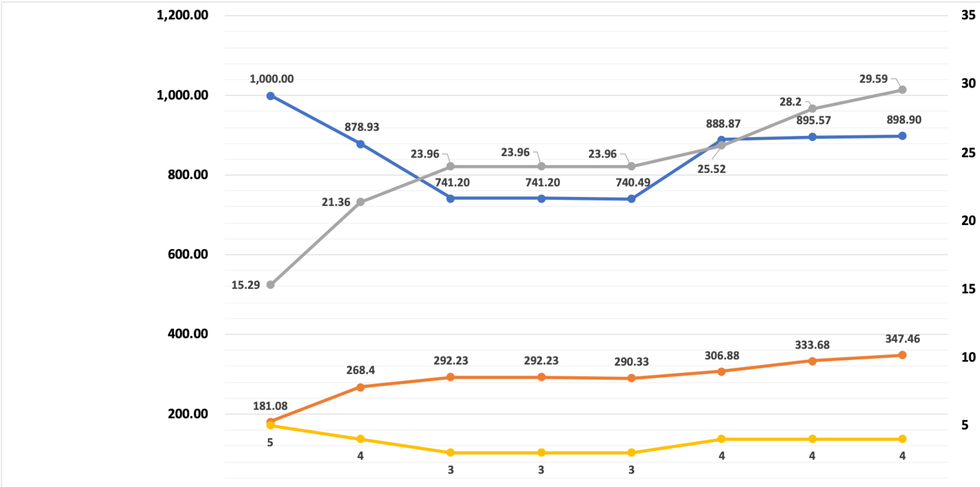
Based on the obtained optimal solution result from individual solving the objective function (6.2), the total time for victims evacuation 367.58 hours is defined as the ϵ_2 which is the right-hand side of equation (6.14) for latterly solving the multi-objective optimization model with Epsilon Constraint method.

In this study, the multi-objective optimization for shelter location-allocation is solved varies upon adjusting the values of maximum acceptable distance between affected area i and shelter j (m_{ij}) between 30 - 65 kilometers. Adjusting the right-hand side values of the particular constraint to observe how the objective function changes is known as "Sensitivity Analysis". Here, the Pareto solution varies upon different m_{ij} generated by solving multi-objective optimization are shown in Table 6.3.

Figure 7.1.4 demonstrates the Pareto optimal results indicate that, when

Table 6.3: Pareto solution for shelter location-allocation varies on max. acceptable distance value

m_{ij}	Total cost (THB)	Total evacuation time (Hours)	Avg distance A-S (km)	No. of shelters	Shelter allocation
30	999,996	181.08	15.29	5	S3: A4, A8 S12: A1 S13: A3, A10 S19: A2, A9 S20: A5, A6, A7
35	878,927	268.4	21.36	4	S1: A1, A4 S13: A10 S19: A2, A3, A9 S20: A5, A6, A7, A8
40	741,199	292.23	23.96	3	S1: A1, A4, A10 S19: A2, A3, A9 S20: A5, A6, A7, A8
45	741,199	292.23	23.96	3	S1: A1, A4, A10 S19: A2, A3, A9 S20: A5, A6, A7, A8
50	740,486	290.33	23.96	3	S1: A4, A5, A10 S19: A2, A3, A9 S20: A1, A6, A7, A8
55	888,865	306.88	25.52	4	S1: A4, A5 S18: A1 S19: A2, A3, A9 S20: A6, A7, A8, A10
60	895,565	333.68	28.2	4	S1: A4, A5 S18: A1 S19: A2, A9 S20: A3, A6, A7, A8, A10
65	898,896	347.46	29.59	4	S15: A4 S18: A1 S19: A2, A5, A9 S20: A3, A6, A7, A8, A10



Max. Acceptable distance	30	35	40	45	50	55	60	65
Total cost (K THB)	1,000.00	878.93	741.20	741.20	740.49	888.87	895.57	898.90
Total evacuation time (Hours)	181.08	268.4	292.23	292.23	290.33	306.88	333.68	347.46
Avg distance A-S (km)	15.29	21.36	23.96	23.96	23.96	25.52	28.2	29.59
No. of shelters	5	4	3	3	3	4	4	4

Figure 6.2: Total cost, total evacuation time, number of open shelters, and average distance varies on max. acceptable distance between affected area and shelter

m_{ij} is relaxed, the average distance between affected areas and selected shelters tend to increase. Likewise, the total time for victims evacuation increase when m_{ij} are loosened as well. However, the results reveal that, relaxing the m_{ij} has no significant effect in reducing the total cost. Furthermore, the number of open shelters do not decrease when permit the m_{ij} to be loosened. Based on the conducting the numerical experiment, it also helps to decide an appropriate strategy to define the proper maximum acceptable distance between affected area and shelter. Herein, the proper maximum acceptable distance should not greater than 50 kilometers since it generates the lowest total cost 740,486 THB, the number of open shelter is 3, with the acceptable total time for victims' evacuation 290.33 hours.

6.4.2 Numerical experiment results of the second echelon

After shelter location-allocations varies on different maximum acceptable distances are know, selecting the location of distribution centers and allocate to open shelters are subsequently determined. The objective function (6.15) is solved with the restrictions of distance between selected distribution center and open shelter (m_{kl}) not exceed 50 kilometers, and each distribution center can serve not over 3 shelters. The location-allocation of distribution centers for serving open shelters are illustrated in Table 6.4.

6.4.3 Total cost along the relief supply chain

Since the location-allocation of both shelter and distribution are determined. The total cost along the relief supply chain can be estimated. The cost estimation is considered based on the total cost that combines fixed cost for opening shelters, victim's transportation cost and service cost along with the transportation cost between open shelters and distribution centers. The total cost can be demonstrated in Table 6.5. Regarding the numerical experiment, it is clearly seen that with the maximum acceptable distance between the affected areas and shelters not exceed 50 kilometers, it generates the lowest total cost of the relief supply chain. Likewise, the results of shelter location-allocation in the first echelon, it was found that restricts the maximum acceptable distance, not over 50 kilometers generate the lowest total cost.

Table 6.4: Distribution center location-allocation

m_{ij}	Open shelters	Distribution center location-allocation	Avg distance S-DC (km)	Transportation cost (THB)
30	S3: A4, A8	DC3	5.63	10,125
	S12: A1	DC3		
	S13: A3, A10	DC3		
	S19: A2, A9	DC1		
	S20: A5, A6, A7	DC2		
35	S1: A1, A4	DC3	6.45	11,610
	S13: A10	DC3		
	S19: A2, A3, A9	DC1		
	S20: A5, A6, A7, A8	DC2		
40	S1: A1, A4, A10	DC3	4.37	7,857
	S19: A2, A3, A9	DC1		
	S20: A5, A6, A7, A8	DC3		
45	S1: A1, A4, A10	DC3	4.37	7,857
	S19: A2, A3, A9	DC1		
	S20: A5, A6, A7, A8	DC3		
50	S1: A4, A5, A10	DC3	4.37	7,857
	S19: A2, A3, A9	DC1		
	S20: A1, A6, A7, A8	DC3		
55	S1: A4, A5	DC3	4.43	7,965
	S18: A1	DC3		
	S19: A2, A3, A9	DC1		
	S20: A6, A7, A8, A10	DC2		
60	S1: A4, A5	DC3	4.43	7,965
	S18: A1	DC3		
	S19: A2, A9	DC1		
	S20: A3, A6, A7, A8, A10	DC2		
65	S15: A4	DC3	3.4	6,282
	S18: A1	DC3		
	S19: A2, A5, A9	DC1		
	S20: A3, A6, A7, A8, A10	DC2		

Table 6.5: Total cost along the supply chain

Mij	Shelter location-allocation	Distribution center location-allocation	Total cost (THB)
30	S3: A4, A8 S12: A1 S13: A3, A10 S19: A2, A9 S20: A5, A6, A7	DC3 DC3 DC3 DC1 DC2	1,010,121
35	S1: A1, A4 S13: A10 S19: A2, A3, A9 S20: A5, A6, A7, A8	DC3 DC3 DC1 DC2	890,537
40	S1: A1, A4, A10 S19: A2, A3, A9 S20: A5, A6, A7, A8	DC3 DC1 DC3	749,056
45	S1: A1, A4, A10 S19: A2, A3, A9 S20: A5, A6, A7, A8	DC3 DC1 DC3	749,056
50	S1: A4, A5, A10 S19: A2, A3, A9 S20: A1, A6, A7, A8	DC3 DC1 DC3	748,343
55	S1: A4, A5 S18: A1 S19: A2, A3, A9 S20: A6, A7, A8, A10	DC3 DC3 DC1 DC2	896,830
60	S1: A4, A5 S18: A1 S19: A2, A9 S20: A3, A6, A7, A8, A10	DC3 DC3 DC1 DC2	903,530
65	S15: A4 S18: A1 S19: A2, A5, A9 S20: A3, A6, A7, A8, A10	DC3 DC3 DC1 DC2	905,178

6.5 Conclusion

This study proposed the two-echelon relief facility location-allocation model. The first echelon involves justifying shelter location-allocation. The proposed model considers two criteria i.e. 1) total cost which includes the fixed cost for open shelter, victims' transportation cost and service cost, and 2) total victims evacuation time. Since the proposed model is a multi-objective function, the Epsilon Constraint method is employed to solve the model. In this study, minimizing the total cost is selected to be the primary, while minimizing the total time for victim evacuation is altered to be the constraint of the primary objective function. The sensitivity analysis is also conducted in order to observe how the objective function change when a particular constraint is adjusted. In this case, the maximum acceptable distance constraint between the affected area and shelter is restricted between 30 - 65 kilometers is selected to perform.

After the locations of shelters are defined, selecting the appropriate distribution centers is then determined. In the second echelon which relates to deciding distribution center location-allocation, the proposed model seeks to minimize the total transportation cost between selected distribution centers and open shelters during disaster occurrence. Then, the total cost along the relief supply chain is determined.

In this study, the proposed model in both echelons is tested with the flood case study in Tha Uthae, Surat Thani, Thailand. The proposed two-echelon facility location-allocation model would benefit to the decision-makers to efficiently and effectively deal with the disaster both response phase and preparation phase.

The originality of this study mainly relates to model formulation which considering both efficient and effective criteria in which the prior work mostly ignored determining simultaneously. Furthermore, the proposed model does not only seek to improve a particular echelon but includes two-echelon i.e. preparedness phase and response phase of disaster management. This study defines the weak points of the solution methods involve weight assignment for addressing multi-objective optimization for location-allocation under the context of humanitarian relief logistics. The more informative and effective method i.e. Epsilon Constraint is employed to deal with the bi-objective optimization problem to avoid identifying the preference values which lead to face with ambiguity in decision making and to evade assigning weight coefficient to the incomparable objective function, especially monetary and non-monetary criteria in which the prior works did not take into account this matter.

However, this study still has a limitation i.e. the proposed model is formulated based on flood characteristics. Therefore, it would be difficult to apply to other types of disasters. For the future study, the uncertainty in terms of disaster's severity to include in the model in order to efficiently and effectively apply for solving real-world problems.

Chapter 7

Conclusion, Contribution, and Future Work

7.1 Research conclusion

This dissertation proposed the methodologies to determine appropriate manners of shelter location-allocation in responding to humanitarian logistics. Several models are formulated as a guideline for decision-makers to justify which shelters should be opened to serve the victims in the aftermath of the disaster, and identify how the opened shelters should be assigned to the affected areas. The conclusion of each model can be summarized as follows:

7.1.1 Efficient shelter location-allocation model:

This model is a single objective optimization model seeks to minimize the total cost of opening shelters, victims' evacuation cost, and victims' service cost. The Genetic Algorithm is used to solve the proposed model. The highlight of this model is a considering of the cost which is an important criterion that reflects how well resource utilization. Without cost determination, the decision-makers would not adequately plan the required budget for victims' relief purposes. The application of the model is validated with a case study of shelter allocation in responding to flood in Tha Uthae, Surat Thani, Thailand. The results generated by the proposed method outperform the current shelter location-allocation determined by a government agency. However, this proposed methodology still has some limitations i.e. the distance between affected areas and candidate shelters is approximated based on the Euclidean distance in which could not perfectly reflect the actual road network distance and only one criterion that is considered.

7.1.2 Multi-objective optimization model for shelter location-allocation:

This model seeks to improve both efficient and effective criteria concurrently in which prior works usually proposed the single-objective function and ignore to consider these two criteria together. There are three objective functions i.e. minimize total cost, minimize total evacuation time, and minimize the number of selected shelters. Unlike prior works, this study presents a concept to determine the proper minimum distance between the affected area and candidate shelter based on the number of victims and population density of each area. The Epsilon Constraint method is adopted to solve the proposed multi-objective since it avoids assigning the weight to monetary and non-monetary objective functions. The Pareto optimal generated by Epsilon Constraint method and optimal solution generated by individually solve single objective function is then compared. The applicability of the proposed model is illustrated through the case study of shelter allocation in responding to the flood in Tha Uthae, Surat Thani of Thailand.

7.1.3 A novel approach for determining shelter location-allocation in humanitarian relief logistics:

This model begins with formulating multi-objective optimization model to minimize total cost and minimize total evacuation time. The optimal solutions generated by the Epsilon Constraint method are latterly simulated and brought to classify shelter allocation by ANN. The ANN model with the proper learning rate is adopted to train and test the dataset. Then, the shelter allocation results generated by both Epsilon Constraint and ANN are compared. The obtained results from ANN quite consistent with the Epsilon Constraint method both in aspects of total cost per person and total evacuation time. However, ANN outperforms the optimization-based method in some cases. The novelty of this model can is demonstrated through the integration of ANN with the Epsilon Constraint method for decision-making on location-allocation problems. To the best of our knowledge, there are no prior works propose and employ to deal with location-allocation problem in context of humanitarian logistics. However, this novel approach still has a limitation. The simulated dataset obtained from solving multi-objective optimization model is considered only the case study affected area. It may not compatible with other case studies that have different characteristics. Yet, this novel approach would be advantageous for decision-makers of these 96 areas when they make decisions on shelter allocation in the future.

7.1.4 Two-stage facilities location-allocation model in responding to relief supply chain:

This model proposes a two-echelon relief facility location-allocation. First echelon involves justifying shelter location-allocation that generates minimum total cost and evacuation time. The second echelon relates to determining distribution center location-allocation to serve all opened shelters. The formulated model attempts to minimize the total transportation cost between selected distribution centers and open shelters during disaster occurrence. Then, the total cost along the relief supply chain is determined. The application of the proposed model is tested by the case study of shelter, and distribution center location-allocation during the flood in Tha Uthae, Surat Thani, Thailand. The originality of this study mainly relates to the model formulation which considering both efficient and effective criteria of multi-echelon in which the prior work mostly ignored determining simultaneously. However, the limitation of this study still exist. However, this model is formulated based on flood characteristics. So, it would not appropriate to apply to other types of disasters. For the future study, the uncertainty in terms of disaster's severity would be included in the model for solving real-world problems.

Conclusion of above-mentioned models aligning by the research goals can be summarized as follows:

Table 7.1 Conclusion of the proposed models align by research goal

Model	Research goal fulfillment	Objective function(s) of each model	Solutions	Applicability	Results
M1	➢ **GOAL 1:** Propose the models to simplify decision-making on shelter location-allocation.	- Min. total cost	GA	Flood case study - 10 areas - 20 shelters	- Results generated by proposed models outperform the current shelter allocation plan.
M2	➢ **GOAL 1:** Propose the models to simplify decision-making on shelter location-allocation.	- Min. total cost - Min. total evacuation time - Min. No. of open shelters	EC, GP	Flood case study - 10 areas - 20 shelters	- Results generated by proposed models outperform the current shelter allocation plan. - Results generated by EC outperform the results produced by GP.
M3	➢ **GOAL 1:** Propose the models to simplify decision-making on shelter location-allocation. ➢ **GOAL 2:** Propose novel approach for support fast decision-making on shelter location-allocation.	- Min. total cost - Min. total evacuation time	EC, ANN-EC	Flood case study - 96 areas - 83 shelters	- Results generated by EC and ANN-EC are quite a consistency. - Results generated by both EC, and ANN-EC outperforms baseline.
M4	➢ **GOAL 1:** Propose the models to simplify decision-making on shelter location-allocation.	- Min. total cost - Min. total evacuation time - Min. distribution cost	EC	Flood case study - 10 areas - 20 shelters	- Relief facilities allocation i.e., shelters and distribution center along the relief supply chain is proposed.

7.2 Contribution

The contribution of this dissertation is divided into three parts i.e.theoretical contribution, practical contribution, and contribution to knowledge science as follows:

7.2.1 Theoretical contribution:

Decision-making on shelter site selection and allocation is normally conducted by the optimization method. This study proposed optimization models to improve monetary and non-monetary terms concurrently. Regarding the literature review, the prior works rather focus on improving either efficiency or effectiveness and employ weight assignment solution approach i.e. Weighted Sum Method, and Weighted Goal Programming to solve the proposed models. In the context of humanitarian logistics, monetary and non-monetary are incomparable and cannot define its importance through the given weights. Hence, the powerful solution approach Epsilon Constraint method is adopted to solved multi-objective optimization models in this study. To advance the decision-making of shelter location-allocation, this study integrates the Artificial Neural Network to deal with complex and large-scale data for solving location-allocation problems in humanitarian logistics field which recognized as the main contribution of this research.

7.2.2 Practical contribution:

The proposed multi-objective optimization models provide decision-making support to decision-makers or related government sectors to determine appropriate shelter location-allocation for responding to the flood onsets. Instead of allocating shelters relying on administrative areas or based on adhoc decision-making, the proposed models help decision-makers to assign the shelters to all affected area with the minimum total cost, minimum total evacuation time, and all victims can access to the alleviate throughout. Furthermore, the novel approach which combines optimization-based and machine learning for justifying shelter allocation simplifies the decision-making process to be more effective when dealing with large-scale data and complex decision-making in the future.

7.2.3 Contribution to knowledge science:

This study creates the knowledge by gathering data, information, and existing knowledge to formulate the mathematical models for solving real-world problems of shelter location-allocation. The proposed models are solved by optimization techniques to generate the optimal solutions. The obtained optimal solutions are interpreted to create the new knowledge and represent through the proper measures to deal with decision-making on shelter location-allocation for the benefit of stakeholders in relief supply chain.

In addition to proposed models, the contribution of this study involves proposing the new approach for dealing with location-allocation problem.

The optimization technique (Epsilon Constraint method) is integrate with machine learning algorithm (Artificial Neural Network). It concerns with allowing machine learning i.e. Artificial Neural Network to learn the knowledge which generated by Epsilon Constraint method

In addition to proposed models, the contribution of this study involves proposing a new approach by integrating Epsilon Constraint method and Artificial Neural Network to deal with location-allocation problem. In this case, ANN is allowed to learn the optimal solutions which are the knowledge that generated by Epsilon Constraint. The ANN will learn how the shelters are assigned to all affected areas under the several patterns of disaster onsets. The novel approach helps decision-makers to determine shelters location-allocation faster than optimization technique. It also supports prompt decision-making which is very important to disaster response process.

7.3 Future works

This study plan to extend the proposed mathematical models to the stochastic facility location-allocation models. The uncertainty parameters such as disaster risk levels or uncertainty demand will be included in the mathematical models. It would improve decision-making on location-allocation problems in real situations. Furthermore, the proposed novel approach for dealing with location-allocation will be tested with other case studies in order to improve the method for determining location-allocation problems continuously.

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Publications

Main publications

International journal

1. **Praneetpholkrang, P.**, Huynh, V. N., Kanjanawattana, S. (2021). A Multi-objective Optimization Model for Shelter Location-allocation in Response to Humanitarian Relief Logistics. The Asian Journal of Shipping and Logistics, In press. https://doi.org/10.1016/j.ajsl.2021.01.003

2. **Praneetpholkrang, P.**, & Kanjanawattana, S. (2021). A Novel Approach for Determining Shelter Location-Allocation in Humanitarian Relief Logistics.*International Journal of Knowledge and Systems Science*. 12(2).

3. **Praneetpholkrang, P.**, Youji, K., Kanjanawattana, S., & Huynh, V. N. Two-Echelon Relief Facility Location-Allocation Model for Humanitarian Supply Chain. Status: Plan to submit to *International Journal of Logistics Research and Applications*.

International conference

1. **Praneetpholkrang, P.**, Huynh, V. N., Kanjanawattana, S. (2021). Bi-objective Optimization Model for Determining Shelter Location-allocation in Humanitarian Relief Logistics. The 10th International Conference on Operations Research and Enterprise Systems, 387–393. https://doi.org/10.5220/0010183503870393

2. **Praneetpholkrang, P.**, & Huynh, V. N. (2020). Shelter Site Selection and Allocation Model for Efficient Response to Humanitarian Relief Logistics. The 7th International Conference on Dynamics in Logistics, 12-14 February 2020, Bremen, Germany, in Dynamic in Logistics, Lecture Notes in Logistics (pp. 309–318). Springer.

Other publications

International journal

1. Sangbamrung, I., **Praneetpholkrang, P.**, & Kanjanawattana, S. (2020). A Novel Automatic Method for Cassava Disease Classification Using Deep Learning. *Journal of Advances in Information Technology*, 11(4), 241-248. https://doi.org/10.12720/jait.11.4.241-248.

International conference

1. Sangbamrung, I., **Praneetpholkrang, P.**, & Kanjanawattana, S. (2020). A Novel Automatic Method for Cassava Disease Classification Using Deep Learning. In 2020 9th International Conference on Information and Electronics Engineering. Tokyo, Japan.

2. Kittichaiwatthana, P., **Praneetpholkrang, P.**, Kanjanawattana, S. (2020). Facial Expression Recognition using Deep Learning. In SUT International Virtual Conference on Science and Technology. Nakhon Ratchasima, Thailand.

Appendix

Report of interview decision-maker in disaster relief

Interviewee: Mr. Amnuay Praneetpholkrang, the Expert Committee of Nakhon Ratchasima Municipality, Thailand who involved and experienced in determining the action plan to response to flood.

Date of interview: October 2020, Thailand

Questions and responses

Q1: What party takes the responsibility in decision-making for response to flooding?

R1: Normally, the provincial office collaborates with the municipality. Department of Disaster Prevention and Mitigation which is one section of the municipality directly involve in rescue, prevent, and mitigate which cause by fire, flood, earthquake, building collapse, as well as other disasters. This section also involves in preparing manpower and equipment to help the victims in a timely manner regarding to the legal regulations.

Q2: About the rescue process which involves evacuating the victims from affected areas to safe zones, what party take the action in this process?

R2: There are several parties get involves in evacuating process. Other than the Department of Disaster Prevention and Mitigation section, the Royal Thai Army is another sector that assists in evacuation process by allocating manpower and vehicles to mobilize the victims to the assigned shelters.

Q3: In terms of facilities for rescue evacuate the victims. What vehicles that are used in evacuation process? What is the specifi-

cation of the vehicles? How many vehicles normally available for evacuation process?

R3: The vehicles that ever used in evacuation process belong to the Royal Thai Army. The further information about the specification can be found in the manual “Vehicle used in the Thai Army (in Thai Language)”. Basically, the required vehicles for evacuating the victims should be 3-5 vehicles.

The employed solver What'sBest! Lindo Optimization

```
What'sBest!® 16.0.2.6 (Mar 17, 2020) - Lib.: 12.0.3977.168 - 32-bit - Status Report -
- Eval Use Only -

DATE GENERATED:                 Jul 19, 2020                    05:07 PM


MODEL INFORMATION:

  CLASSIFICATION DATA              Current     Capacity Limits
  --------------------------------------------------------
  Total Cells                          494
    Numerics                           469
      Adjustables                       25                300
        Continuous                       0
        Free                             0
        Integers/Binaries             0/25                 30
      Constants                        413
      Formulas                          31
    Strings                              0
    Constraints                         25                150
  Nonlinears                            25                 30
  Coefficients                         196

  Minimum coefficient value:         0.3333333333333  on เมือง.วัดประดู่!Q72
  Minimum coefficient in formula:    เมือง.วัดประดู่!Q76
  Maximum coefficient value:         3000  on <RHS>
  Maximum coefficient in formula:    เมือง.วัดประดู่!W55

MODEL TYPE:                     Mixed Integer / Nonlinear (Mixed Integer Nonlinear Program)

SOLUTION STATUS:                LOCALLY OPTIMAL (see messages below)

OPTIMALITY CONDITION:           SATISFIED

OBJECTIVE VALUE:                0.0

BEST OBJECTIVE BOUND:           0.0

OPTIMALITY TOLERANCES:          0.00001

INFEASIBILITY:                  0.0

DIRECTION:                      Minimize

SOLVER TYPE:                    Branch-and-Bound

ITERATIONS:                     124.0
```

```
STEPS:                          1.0

ACTIVE:                         0.0

SOLUTION TIME:                  0 Hours  0 Minutes  4 Seconds
Extracting Data                 0 Hours  0 Minutes  0 Seconds
Storing Relevant Formulas       0 Hours  0 Minutes  0 Seconds
Building the Model              0 Hours  0 Minutes  0 Seconds
Solving                         0 Hours  0 Minutes  4 Seconds

NON-DEFAULT SETTINGS:

  WBBIN Range:    Detected

ERROR / WARNING MESSAGES:

***WARNING***
  Nonlinearities Present (Help Reference: NLINCELL):
  The cells below contain nonlinear expressions. If these cells are used only for
  reporting, then, for efficiency, they should be included in a WBOMIT range (refer
  to documentation). In some cases, nonlinear cells may be linearized automatically
  by the Linearization option that is set in the General Options dialog box. This
  warning can be turned off with the Nonlinearity Present checkbox in the
  General Options dialog box
  (cell addresses listed at bottom of tab).

LISTING:

***WARNING***
  List of nonlinear expressions:
เมือง.วัดประดู่!Q74          เมือง.วัดประดู่!R74          เมือง.วัดประดู่!S74          เมือง.วัดประดู่!T74
เมือง.วัดประดู่!U74

***WARNING***
  List of contributors to nonlinear cells:
เมือง.วัดประดู่!Q55          เมือง.วัดประดู่!R55          เมือง.วัดประดู่!S55          เมือง.วัดประดู่!T55
เมือง.วัดประดู่!U55          เมือง.วัดประดู่!Q56          เมือง.วัดประดู่!R56          เมือง.วัดประดู่!S56
เมือง.วัดประดู่!T56          เมือง.วัดประดู่!U56          เมือง.วัดประดู่!Q57          เมือง.วัดประดู่!R57
เมือง.วัดประดู่!S57          เมือง.วัดประดู่!T57          เมือง.วัดประดู่!U57          เมือง.วัดประดู่!Q58
เมือง.วัดประดู่!R58          เมือง.วัดประดู่!S58          เมือง.วัดประดู่!T58          เมือง.วัดประดู่!U58
เมือง.วัดประดู่!Q59          เมือง.วัดประดู่!R59          เมือง.วัดประดู่!S59          เมือง.วัดประดู่!T59
เมือง.วัดประดู่!U59

End of Report
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