LARGE-SCALE EVACUATION NETWORK MODEL FOR TRANSPORTING EVACUEES WITH MULTIPLE PRIORITIES

A Thesis

by

HYEONG SUK NA

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Chair of Committee,	Amarnath P. Banerjee
Committee Members,	Justin T. Yates
	Luca Quadrifoglio
Head of Department,	César O. Malavé

May 2014

Major Subject: Industrial Engineering

ABSTRACT

There are increasing numbers of natural disasters occurring worldwide, particularly in populated areas. Such events affect a large number of people causing injuries and fatalities. With ever increasing damage being caused by large-scale natural disasters, the need for appropriate evacuation strategies has grown dramatically. Providing rapid medical treatment is of utmost importance in such circumstances. The problem of transporting patients to medical facilities is a subject of research that has been studied to some extent. One of the challenges is to find a strategy that can maximize the number of survivors and minimize the total cost simultaneously under a given set of resources and geographic constraints. However, some existing mathematical programming methodologies cannot be applied effectively to such large-scale problems.

In this thesis, two mathematical optimization models are proposed for abating the extensive damage and tragic impact by large-scale natural disasters. First of all, a mathematical optimization model called Triage-Assignment-Transportation (TAT) model is suggested in order to decide on the tactical routing assignment of several classes of evacuation vehicles between staging areas and shelters in the nearby area. The model takes into account the severity level of the evacuees, the evacuation vehicles' capacities, and available resources of each shelter. TAT is a mixed-integer linear programming (MILP) and minimum-cost flow problem. Comprehensive computational experiments are performed to examine the applicability and extensibility of the TAT model.

Secondly, a MILP model is addressed to solve the large-scale evacuation network problem with multi-priorities evacuees, multiple vehicle types, and multiple candidate shelters. An exact solution approach based on modified Benders' decomposition is proposed for seeking relevant evacuation routes. A geographical methodology for a more realistic initial parameter setting is developed by employing spatial analysis techniques of a GIS. The objective is to minimize the total evacuation cost and to maximize the number of survivors simultaneously. In the first stage, the proposed model identifies the number and location of shelters and strategy to allocate evacuation vehicles. The subproblem in the second stage determines initial stock and distribution of medical resources. To validate the proposed model, the solutions are compared with solutions derived from two solution approaches, linear programming relaxation and branch-and-cut algorithm. Finally, results from comprehensive computational experiments are examined to determine applicability and extensibility of the proposed model.

The two evacuation models for large-scale natural disasters can offer insight to decision makers about the number of staging areas, evacuation vehicles, and medical resources that are required to complete a large-scale evacuation based on the estimated number of evacuees. In addition, we believe that our proposed model can serve as the centerpiece for a disaster evacuation assignment decision support system. This would involve comprehensive collaboration with LSNDs evacuation management experts to develop a system to satisfy their needs.

To my family

사랑하는 가족들에게 바칩니다.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Amarnath P. Banerjee, for his guidance, support, and patience throughout the course of this research. He is a role model for being so humble even when having achieved so much. It is indeed a privilege to work with him. I especially appreciate him trusting me all the time. I am also grateful to my committee members, Dr. Justin T. Yates and Dr. Luca Quadrifoglio, for their guidance and help in my thesis, coursework, and academic career pursuit. Thanks also go to my friends and colleagues for making my time at Texas A&M University a great experience.

My profound appreciation goes to my family. I am so grateful for my wife's everlasting love and endurance. I remember her constant support when I encountered several difficulties. My adorable daughters, Yedam and Yebit, have been a strong force during my graduate studies. I thank my mother and my in-laws for their unconditional support, belief, encouragement, and affection.

Above all, thank you, God. May your name be exalted, honored, and glorified.

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

LIST OF TABLES

Page

CHAPTER I

INTRODUCTION

I.1. Motivation

Natural disasters are often large-scale, rapid-onset, and overwhelming catastrophes relative to the scale of damage and the toll of casualties. On January 12th 2010, an estimated three million people were affected by the Haiti earthquake; approximately 320,000 people died, 300,000 were injured, and over a million people were rendered homeless. The 2011 Tohoku tsunami was responsible for an estimated 16,000 deaths, about 6,150 people were injured, and 2,850 were missing. The tsunami caused nuclear accidents, and many nuclear power generators were taken down. Citizens within 50 miles of the Fukushima Diichi Nuclear Power Plant were urged to evacuate. In November 2013, Typhoon Haiyan (or Typhoon Yolanda in the Philippines) adversely affected a large region of Southeast Asia. In the Philippines, the death toll from the typhoon reached 6,000 along with a large number of people reported missing.

Large-scale natural disasters (LSNDs) have become regular occurrences that result in extensive economic damage as well as significant loss of life or mental injury. The extent of cumulative damage by recent LSNDs is too extreme to be estimated. According to an announcement by the Centre for Research on the Epidemiology of Disasters (CRED) (2012), there was a small decrease (-11.08%) in the number of total people affected by natural disasters in 2011 compared to the annual average from 2001 to 2010. However, in 2011, the natural disaster damage in the world (US$ 362.8 billion) increased by 272.2% compared to the annual average damage from 2001 to 2010 (US$ 97.5 billion). Over the past few years, the growth rate of victims affected by LSNDs has decreased steadily, but rather the estimated damage cost has increased rapidly. This phenomenon of lesser number of affected people is likely due to increased planning and deployment of resources during a disaster to evacuate and save lives effectively. Governments and other agencies bear a significant amount of cost to perform these actions. Therefore, efficient preparation plans and tactical evacuation strategies against natural disasters can reduce the total evacuation cost and increase the total survivors, simultaneously.

Disasters are unstructured in scope and they are often unpredictable in regard to scale, timing, impacts and consequent catastrophes, especially LSNDs. To cope with the residual effects of LSNDs, the systematic organization of people, labor and available resources is requested. Howitt and Leonard (2006) propose four domains in order to improve disaster response effectively: Capabilities, Structures and Systems, People, and Coordination. In order to cope with LSNDs appropriately, optimal evacuation routes, adequate traffic control policies, and sufficient medical equipment and relief supplies are positively necessary with the capacity to maintain themselves in the disaster affected areas within a reasonable time period. Many of the relief resources used during disaster response are expensive and not always used or consumed on a regular basis. Maintaining such relief resources at every potential disaster area is inefficient and not cost effective. In order to adequately handle the surge in demand during a disaster, the main challenge lies in being able to locate, mobilize, and allocate relief resources quickly. The other challenges are to coordinate their use effectively upon arrival at a disaster scene and to transport evacuees to safe shelters. This is significant since disaster evacuations give rise to surplus traffic flow, mostly against available network capacity. In conclusion, decision-makers for disaster risk management face numerous challenges when determining how to transport evacuees efficiently, find the best evacuation routes from affected areas to safe shelters, and distribute indispensable medical resources to the right shelter at the right time.

I.2. Research objective and overview

The World Health Organization (WHO) (1995) defines a disaster as any occurrence that causes damage, ecological disruption, loss of human life, or deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area. The US Federal Emergency Management Agency (FEMA) (2012) describes it as an occurrence of a natural catastrophe, technological accident, or human caused event that has resulted in severe property damage, deaths, and/or multiple injuries. The American College of Emergency Physicians (ACEP) (2011) states that a disaster has occurred when the destructive effects of natural or man-made forces overwhelm the ability of a given area or community to meet the demand for healthcare. Disasters are often described as a result of the combination of the exposure to a hazard, the conditions of vulnerability that are present, and insufficient capacity or measures to reduce or cope with the potential negative consequences. In general, disasters may be classified in a variety of ways, but in this thesis, the disasters are classified into two categories: natural and man-made (or technological) disasters.

LSNDs are an unforeseen event occurring directly from natural causes, including but not limited to, hurricane, earthquake, flood, tsunami, volcanic eruption, wildfire or other similar events that result in significant disastrous consequences in terms of human fatalities, injuries, and property damage. In this thesis, two mathematical modeling methods are addressed to lessen the impact of LSNDs. Fig. 1 depicts the thesis overview.

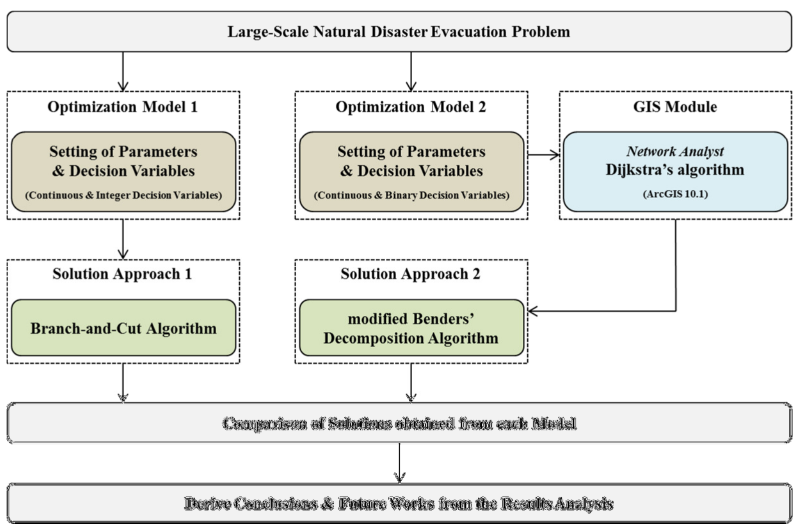

Fig. 1. Thesis overview

In the optimization model 1, in order to describe the LSND evacuation problem, a mixed-integer linear programming (MILP) model is proposed and solved with an exact solution approach such as the branch-and-cut (B&C) algorithm. However, because there are several limitations on the modeling and solution approaches in the model, the optimization model 2 is suggested to overcome the barriers with two-stage optimization modeling method and geographic information system (GIS) techniques. After that, some results are compared, and used for deriving conclusions and future works.

I.3. Organization of this thesis

This thesis introduces a systematic approach for designing and solving LSND evacuation problems using large-scale optimization models and the relevant solution approaches. To understand the features and impacts of the LSND, Chapter II explains the systematic process of disaster risk management, and describes the principal fields of action of this procedure. There are some studies using mathematical modeling, simulation modeling and GIS-based modeling to solve large-scale evacuation problems. These studies along with their advantages and disadvantages are summarized. Finally, the limitations of the existing models are addressed in Chapter II.

Chapter III develops a MILP model for LSND evacuation problem, followed by enhancements to the model to relax the restriction on the number of evacuees that can be transported by evacuation vehicles. Numerical experimentation results and resultant discussions are also provided.

In Chapter IV, the MILP model proposed in Chapter III is extended. The two-stage optimization model is proposed for the efficient evacuation modeling and solution approach after describing the LSND evacuation problem with MILP formally. Chapter IV discusses how BD and GIS methodologies can be applied to the solution approaches for the evacuation network problem. Then computational experiments are conducted for the LSND evacuation problems and several principal results are provided and discussed.

Chapter V is dedicated to several discussions on the computational results analysis after summarizing several findings and offers suggestions for expanding our research to other classes of LSND evacuation modeling. Finally, our conclusions and future works are presented.

CHAPTER II

LITERATURE REVIEW

In this chapter, we review several studies to understand the disaster risk management for the LSND evacuation. To handle the LSNDs more efficiently, various concepts and definitions of disaster life cycle (DLC) are examined. We also investigate diverse LSND evacuation models and compare the advantages and disadvantages of each model. Finally, we find some limitations of existing evacuation models and derive some ideas for a novel modeling method.

II.1. Disaster risk management

The National Oceanic and Atmospheric Administration (NOAA) (2012) reports that each natural disaster of 2011 caused at least $1 billion in damage. According to the CRED report published in 2012, five countries, comprising of the Philippines, the United States, China, India, and Indonesia, accounted for 31% of the total global disaster occurrences in 2011. In addition, seven out of the top 10 countries reporting global disaster mortality are located in Asia, while the other three countries are located in the Americas. The top seven Asian countries account for 83.1% of the fatalities from all the natural disasters. Also, the year 2011 was the most expensive year ever in terms of the economic damage caused by natural disasters; Japan (US$ 212.5 billion), United States (US$ 59.4 billion), Thailand (US$ 40.3 billion), and several other national incidents. Not surprisingly, there appears to be a relationship between the levels to which societies accept the disaster risk management strategies and to which they experience disasters. Consequently, as natural disasters increase, so does the interest in disaster risk management (Drabek, 1986).

Disaster risk management aims to avoid, lessen, or transfer the adverse effects of hazards through activities and measures for prevention, mitigation, and preparedness (ISDR, 2009). A well-planned LSND evacuation strategy is one of the key requirements for successful LSND risk management. A primary component of the LSND evacuation strategy is an effective evacuation policy or system, which plays a dominant role in reducing mortalities and injuries.

According to ISDR Secretariat (2004), the disaster risk management framework is composed of the following main components.

- Political commitment and institutional development (Governance): Defined in terms of political commitment and strong institutions, governance has to lessen the disaster risk, allocate several indispensable relief and medical resources to the right places, take a risk of failure for disaster policies, as well as attract participation from relative organizations.
- Risk identification and assessment: It is relatively clear-cut to identify the scale and outbreak time of natural disasters. Systematic assessment methods of the damage on the natural disasters are also well-organized. It is now imperative to recognize natural disaster occurrences as soon as possible.

- Knowledge management: Information communication strategy, publicity activities and training, and research on the evacuation plan are required to improve knowledge on disaster risk management.
- Risk management applications & instruments: Risk management applications and instruments have been given attention with the recognition of the environment protection policies.
- Disaster preparedness, contingency planning and emergency management: A well-prepared system against disasters can give an early warning, cope with the evacuation procedure for disasters, and make an adequate relief/medical logistics plan.

According to the above framework, disaster risk management is mainly composed of pre- and post-disaster events based on the DLC. Disaster risk management sometimes includes only pre-disaster management strategies, but all phases of disaster risk management have to be evaluated regarding hazard-related losses, economic turmoil and collapse, social consensus as well as medical ethics.

With respect to the many diverse definitions of DLC and an inhomogeneous understanding of the cycle defining terms in literature, this chapter gives a contribution to create a unified language as a basis for communication among stakeholders.

The initial idea of the DLC is introduced by Carr (1932) and considered a four-stage sequence pattern of events such as (i) Preliminary or Prodromal, (ii) Dislocation and Disorganization, (iii) Readjustment and Reorganization, and (iv) Confusion-delay.

For the past three decades, policy makers, educators, practitioners, and researchers in the United States have designed a four-phase model to prepare for and respond to disasters well: (i) Preparedness, (ii) Response, (iii) Recovery, and (iv) Mitigation.

The four-phase model is effective to frame subjects related to disaster preparedness as well as economic restoration after a disaster. Each phase requires evident means, strategies, and resources, and confronts miscellaneous challenges. The four-phase model covers all of the actions described in the abovementioned classification while providing a more focused view of evacuation strategy activities. Moreover, the four-phase classification is based on the Comprehensive Emergency Management concept introduced in the 1978 report of the National Governors' Association (NGA) Emergency Preparedness Project (Altay and Green III, 2006).

Although the four phases are part of the common language and theoretical underpinning of disaster evacuation or emergency management in the U.S., a number of adaptations can be found. Some of the recent changes are subtle and involve only additional words, perhaps to be more descriptive. A disaster cycle has four phases, and all responses must pass through each: Mitigation, Planning, Response, and Recovery (Goolsby, 2011). In Idaho State, Mitigation is changed to Mitigation and Prevention. Another variation is that Planning/Preparedness is replaced by just Preparedness in the City of Winston-Salem.

According to the Johns Hopkins and the International Federation of Red Cross and Red Crescent Societies (2008), the disaster cycle is presented by Mitigation, Preparedness, Response, and Reconstruction (or Rehabilitation). However, Prevention phase can be included as a part of DLC when a disaster cannot be prevented entirely.

The Transportation Research Board (2007) suggests the homeland security all-hazards taxonomy as the cycle, which is Prevent, Protect, Respond, and Recover, in the TR News. Guided by The Texas Homeland Security Strategic Plan 2010-2015 (Perry, 2010), Texas moves forward on a broad front to improve their ability to Prevent, Protect from, Respond to and Recover from all disasters or threats. In recent years, the U.S. Department of Homeland Security (DHS) (2009) and FEMA (2010) have adopted the terms, Resilience and Prevention, as part of the paradigm of disaster evacuation or emergency management. FEMA suggests that emergency planning addresses each of the four mission areas identified in the National Strategy for Homeland Security: to prevent, protect against, respond to, and recover from natural, technological, or human-caused emergencies.

In conclusion, although the four-phase model is a prevalent strategy and provides the theoretical underpinning of disaster risk management, a number of adaptations can be found. Some studies now refer to five or six phases rather than four. Others have changed the descriptive terms for one or more of the phases. Furthermore, a number of government publications examined as part of this research are more confusing than informative. In fact, many of those definitions of DLC show overlap of adjacent phases. This acknowledges that critical activities frequently cover more than one phase, and the boundaries between phases are seldom precise. Most articles also emphasize that important interrelationships exist among all the phases. In this thesis, Mitigation and

Reconstruction (or Recover) phase are regarded as a Resiliency phase and the conceptual diagram (Fig. 2) is helpful in designing a disaster evacuation strategy. In order to improve effective responses of disaster risk management, in this thesis, the three-phase DLC is proposed as follows: Preparedness, Response, and Resiliency (Fig. 3).

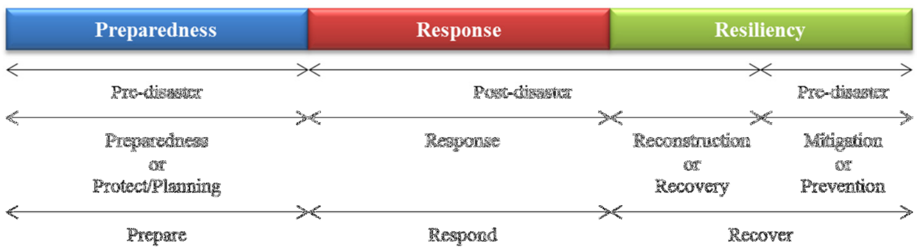

Fig. 2. DLC comparison

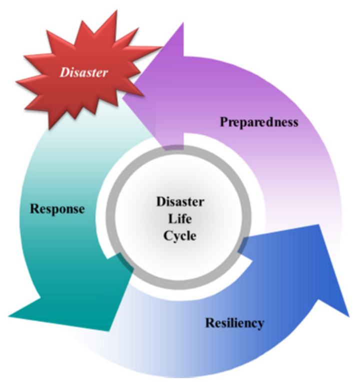

Fig. 3. DLC concept proposed by this thesis

In our proposed concept of DLC, the phases of Preparedness and Response are addressed and focused in this thesis. The following literature reviews are not only related to the phases, but also presented the relevant problem modeling methods and solution approaches for coping with LSNDs.

II.2. Mathematical models for the LSND evacuation

The recent spate of large-scale natural disasters evinces the necessity for planning disaster risk management that focuses on performing strategic evacuation and responding to the catastrophic events in a timely fashion. Despite the critical importance of this issue, we find surprisingly few studies that look at how the allocation of capacity, paired with various types of evacuees and several disaster evacuation vehicles, affects evacuation traffic flow and evacuation efficiency. According to a survey study (Altay and Green III, 2006), only 28.4% of 109 articles related to disaster risk management are about natural disaster evacuation. They also point out that mathematical programming is used as a solution methodology in only 32.1% of the cases.

Several researchers have focused their attention on a large-scale evacuation network model with a wide variety of methodologies including mixed-integer programming (Cova and Church, 1997; Cova and Johnson, 2003; Chen and Miller-Hooks, 2008; Tayfur and Taaffe, 2009; Sayyady and Eksioglu, 2010; Bretschneider and Kimms, 2011; Na and Banerjee, 2012), dynamic programming (Chiu *et al.*, 2007; Andreas and Smith, 2009; Yao *et al.*, 2009; Bish *et al.*, 2014), approximate dynamic programming (Erdelyi and Topaloglu, 2010), stochastic programming (Mete and Zabinsky, 2010; Li *et al.*, 2011; Mclay and Mayorga, 2013), multi-objective optimization (Stepanov and Smith, 2009), and various heuristic techniques (Cova and Church, 1997; Sayyady and Eksioglu, 2010; Xie *et al.*, 2010).

Among many mathematical modeling approaches, the MILP formulation method has been frequently used for a network flow problem or several evacuation problems with integer extension of variables. However, many researchers have pointed out that some computational difficulties can arise in model management or in the solution approach of the model when any type of model becomes quite large. In other words, the expansion of the MILP problem scale generated by the number of variables or constraints often poses a challenge while attempting to solve them. One of the challenges is in the difficulty in solving NP-complete problems using off-the-shelf solvers is the excessive CPU time requirement. Na and Banerjee (2012) address a LSND evacuation problem with MILP and find that the CPU solution time and occupied memory size increases sharply as the size of problem (or the number of variables) rises. Hence, although many LSND evacuation problems are often formulated using a MILP method for better modeling, there are several limitations on the formulation and solution approaches for LSND evacuation problems. This has led to the use of decomposition procedures for obtaining the exact solutions rather than approximate solutions. This is because a very large model may not fit into memory, but the decomposition algorithm can allow the smaller pieces to fit. Consequently, exact solution approaches such as Dantzig-Wolfe decomposition (DWD), Benders' decomposition (BD), and Lagrangian relaxation (LR) have been considered for solving the MILP evacuation problems.

The decomposition algorithm generally involves the iterative solution of the easier subproblem, with adjusted incumbent solutions passed to the subproblem between iterations. The Dantzig-Wolfe algorithm (1960) and Benders' algorithm (1962) are the best-known examples for large-scale optimization models. BD (Benders, 1962) is helpful to efficiently process the large-scale MILP problems that often arise in practical applications. The method partitions the MILP problem into two problems, named master problem and subproblem. The master problem and the subproblem are solved iteratively until the upper and lower bounds are sufficiently close. With the BD techniques, Sherali et al. (1991) address a nonlinear mixed-integer programming evacuation problem, Chen and Miller-Hooks (2008) examine and solve a building evacuation problem with shared information, and Andreas and Smith (2009) consider the design of an evacuation tree.

BD is different from DWD in terms of the decomposed problems. BD splits the variable set into two subsets, but DWD does the constraint set. Thus, BD is often described as DWD applied to the dual of a problem. Tomlin (1966) focuses on a complicated network flow problem with multi-commodities and various costs. In addition, he considers two different forms of node-arc and arc-chain, and shows the two different formulations can be quite equivalent. For very large linear programs, he concludes that the DWD can be regarded as decomposing the node-arc flows into arc-chain flows.

Lagrangian optimization is another popular technique for solving problems with complicating constraints. Xie and Turnquist (2011) have formulated a lane-based evacuation network optimization problem, and developed an integrated LR and tabu search solution method.

Since computational struggles of optimization problems increases significantly with the number of variables and constraints, solving smaller problems iteratively can be more efficient than solving a single large problem (Smith and Sonuc, 2011). However, increasing the number of constraints and variables often leads to deviation from a special or desirable problem structure, thereby limiting the use of decomposition techniques. Finally, these have contributed to the exploration and application of heuristic methods.

Several metaheuristic methodologies have been applied to the disaster evacuation problems with mixed-integer variables, including tabu search (Sayyady and Eksioglu, 2010; Xie et al., 2010; Xie and Turnquist, 2011), genetic algorithm (Teklu et al., 2007; Miller-Hooks and Sorrel, 2008; Ng and Waller, 2010; Berkoune et al., 2012), and ant colony optimization algorithm (Yi and Kumar, 2007; Vitins and Axhausen, 2009; Fang et al., 2011). Nevertheless, the heuristic procedures are not guaranteed to find the global optimum. The heuristic algorithms are used to find approximate solutions for many complicated optimization problems within polynomial time. This makes it difficult to use heuristic procedures if the intent is to obtain a global optimal solution or even a local optimal solution within specified threshold intervals.

When we develop mathematical models for LSND evacuation problems, the dynamic network flow model can be also considered. Several dynamic network flow models for an evacuation problem deal with building evacuation policy, evacuation routing selection, or disaster relief allocating strategy (Chalmet et al., 1982; Jarvis and Ratliff, 1982; Sheffi et al., 1982; Haghani and Oh, 1996; Pidd et al., 1996; Cova and Johnson, 2003; Chiu et al., 2007). Erdelyi and Topaloglu (2010) develop a dynamic model for a capacity allocation problem with multiple priority levels with an approximate dynamic programming (ADP) approach.

In conjunction with evacuation strategies, logistics support problems have been considered extensively in disaster risk management (Yi and Özdamar, 2007). In the beginning of response phase, the evacuation strategies are the most important, but logistics operations for continuous relief and medical supplies are also required necessarily for evacuees or survivors in the damaged region. In order to allocate the medical resources and transport the injured evacuees as timely as possible, quick relief access to affected regions and suitable assignment of evacuation vehicles and safe shelters are required (Sherali et al., 1991; Özdamar et al., 2004; Yi and Özdamar, 2007).

II.3. GIS-based models for the LSND evacuation

Disaster risk management is generally spatial-oriented. Spatial optimization models with GIS technology are considered as an important decision-making method in disaster risk management. All phases of DLC are closely connected with information generated from diverse places and agents. The appropriate information has to be collected, arranged, and shared immediately in order to decide the scale and scope of disaster risk management. Actually, while evacuating a number of evacuees, it is so important to have the accurate information at the right time and to respond appositely against LSNDs. With utilizing a GIS, decision-makers and rescue workers can share requisite information through geographic database systems anywhere. Hence, GIS can provide a mechanism to be concentrated and revealed visually serious issues during LSND evacuation processes (Johnson, 2000).

In particular, in the preparedness and response phase, GIS can play a significant role in the development of intelligent LSND evacuation systems. Dunn (1992) examines the role of GIS in deciding the optimal evacuation paths, De Silva *et al.* (1993) develop and integrate a simulation model into GIS for disaster evacuation planning, and Cova and Church (1997) address a GIS-based method to resolve potential difficulties of disaster risk management before occurring LSNDs. Recently, Crooks and Wise (2013) present an explicit agent-based model using GIS techniques with the scenario of the 2010 Haiti earthquake. The routes of evacuees and the relevant events are examined.

However, there are few previous studies that applied both BD techniques and GIS methodologies to a LSND evacuation problem. In Chapter IV, we develop an MILP formulation for the evacuation and propose a solution framework based on a BD scheme with an embedded GIS module. Such a modeling approach may also enable evacuation planners to evaluate several scenarios of some real-time problems (Cova and Church, 1997; De Silva *et al.*, 2000; Stepanov and Smith, 2009).

CHAPTER III

A DYNAMIC NETWORK EVACUATION MODEL FOR TRANSPORTING MULTIPLE PRIORITY EVACUEES

III.1. Introduction

Natural disasters are unpredictable and unavoidable, and often result in serious damage. Providing rapid medical treatment is of utmost importance in such circumstances. The problem of transporting patients to medical facilities is a subject of research that has been studied to some extent. One of the challenges is to find a strategy that can maximize the number of survivors and minimize the total cost simultaneously under a given set of resources and geographic constraints. Hence, a well-planned disaster risk management can help lessen the adverse effect of the disasters.

For the preparedness and response phases against natural disasters, an evacuation network model is formulated as a large-scale deterministic MILP problem. This model is different from the papers reviewed in Chapter II as follows:

- The proposed model is developed as an MILP formulation for LSND evacuation. A solution approach, B&C algorithm, attempts to obtain the exact solution without the use of decomposition, or relaxation techniques. In this case, a primary consideration is not the extent of CPU usage and time to solve the problem, but rather a reasonable solution within proper error ranges. The time issues and limitations on the proposed model are discussed later.

- There are multiple objectives in the proposed model, which has evacuees with different priorities, various categories of vehicles for transporting evacuees, multiple staging areas for evacuees, and several shelter (e.g., hospital) choices for evacuees. In this model, we focus on (i) the number of evacuees to be transported from staging areas to shelters during the response phase, (ii) assignment of evacuees to shelters, (iii) allocation of evacuation vehicles to evacuees and (iv) allocation of relief resources for evacuees needing emergency medical attention.
- The evacuees have multiple priorities based on the severity level of their injuries. There are also multiple types of evacuation vehicles that have different speeds, transportation costs and capacities, and the types of patients that can be transported. The proposed model tries to solve the allocation-assignment problem for coordinating relief resources support as well as for evacuation operations in disaster response activities considering the conditions of evacuees and evacuation vehicles.

III.2. Mathematical modeling

Herein, a LSND evacuation network problem is addressed with discussions on a model formulation and relevant assumptions. We propose a large-scale deterministic MILP model based on the minimum-cost flow model, referred to as Triage-Assignment-Transportation (TAT). The objective of TAT model is to minimize the total medical and transportation cost for disaster evacuation, and simultaneously to maximize the number of evacuees meeting all conditions and restrictions in a capacitated network. The TAT model takes into account (1) the severity levels or transportation priorities of evacuees, (2) the types of evacuation vehicles, (3) the capability and speed of evacuation vehicles, (4) medical costs of the shelters and (5) setup costs to be transformed for other facilities except hospitals to an evacuation shelter. Shelters refer to hospitals and other facilities providing medical care in this model. The affected people at the staging areas are referred to as evacuees, while the evacuees that have arrived at a shelter are designated as patients. This provides a clear distinction of the affected people based on location. Finally, we examine significant aspects of the model's structure, followed by the discussion on the relaxation of some restrictions of the primal modeling.

III.2.1. Primal modeling

The assumptions of the TAT model are as follows:

- In the TAT model, the cost is classified into two categories: medical and transportation cost. The medical cost is generated when an evacuee is waiting for evacuation vehicles at a staging area or being transported to a shelter. The medical cost can be variable based on the severity level of evacuees, waiting and transportation time as well as the amount of using medical resources. In addition, the transportation cost is incurred as an evacuation vehicle transports evacuees between staging areas and shelters. The transportation cost is decided by the evacuation vehicles' type, distance and traffic congestion of the evacuation routes, and/or evacuees' priority.

- Prior to the LSND, the evacuation vehicles are assumed to be located in their respective home locations. The initial transportation time and cost of evacuation vehicles moving from their home location to the staging area is ignored in this model. The transportation cost and time are measured from the first evacuation traffic originating from the staging area.
- All patients have completed a triage process, such as START (Simple Triage and Rapid Treatment) or SALT (Sort-Assess-Lifesaving Interventions-Treatment/Transport). At a staging area, a result of a triage process will indicate the priority of an evacuee. In general, the evacuees with the highest-priority are transported to shelters first.
- Additional medical resources such as physicians and nurses, referred to as practitioners in this thesis, can be mobilized from their home institutions to the shelters for providing medical care to the evacuees.
- The time unit is measured in minutes, and all the time dependent parameters are expressed as a multiple of this time unit.

The decision variables of the TAT model are as follows:

X_{ijkp}^{t} = 1 if evacuation vehicle k is assigned to p-priority evacuee(s) on an evacuation arc (i, j) at time t; = 0 otherwise

Y_{jikp}^{t} = 1 if evacuation vehicle k is assigned to p-priority evacuee(s) on an evacuation arc (j,i) at time t; = 0 otherwise

Z_{ljp}^{t} Number of practitioners moved from institution l to shelter j for p-priority patient(s) at time t

RP_{ip}^{t} Number of p-priority evacuees remaining in staging area i at time t

SV_{ik}^{t} = 1, if evacuation vehicle k is at staging area i at time t; = 0 otherwise

HV_{jk}^{t} = 1, if evacuation vehicle k is at shelter j at time t; = 0 otherwise

RD_{lp}^{t} Number of practitioners available to take care of p-priority patients in institution l at time t

V_{lp}^{+} Surplus number of practitioners available for p-priority patients in institution l after evacuation

V_{lp}^{-} Shortage number of practitioners requested for p-priority patients in institution l after evacuation

RB_{jp}^{t} Number of beds for p-priority patients in shelter j at time t

U_{jp}^{+} Surplus number of beds available for p-priority patients in shelter j after evacuation

U_{jp}^{-} Shortage number of beds required for p-priority patients in shelter j after evacuation

The formulation of TAT model is shown here followed by a narrative of the objective function and the constraints.

Objective Function

$$Minimize \quad \sum_{i,j,k,p,t}\left[f_1(i,j,k,p,t)+f_2(i,j,k,p,t)\right]+\sum_{l,j,p,t} f_3(l,j,p,t) \tag{1}$$

The objective (1) aims at minimizing the total evacuation costs, by considering the medical expense of evacuees with multiple priorities $(f_1(i,j,k,p,t))$, the transportation and standby cost of evacuation vehicles with multiple types $(f_2(i,j,k,p,t))$, the management cost of practitioners for taking care of patients in shelters $(f_3(l,j,p,t))$, and the surplus and shortage costs for medical resources (e.g., beds) after the evacuation is completed $(f_3(l,j,p,t))$.

When evacuees are given emergency treatment at staging areas or transported from staging areas to shelters, the medical expense is defined as follows:

$$f_1(i,j,k,p,t)=\sum_{i,p,t}\left(\varsigma_p \cdot RP_{ip}^t\right)+\sum_{i,j,k,p,t}\left(w_{kp}\cdot \kappa_{kp}\cdot X_{ijkp}^t\right), \tag{2}$$

where ς_p is the unit cost (*$/evacuee/minute*) for taking care of a *p*-priority evacuee at a staging area, w_{kp} is the unit cost (*$/evacuee*) for taking care of a *p*-priority evacuee during transportation, and the maximal seating capacity (κ_{kp}) of an evacuation vehicle *k*. The capacity (κ_{kp}) is variable according to the priority of evacuees and the evacuation vehicle's type. In the primal TAT model, we assume that the number of evacuees accommodated by an evacuation vehicle is same as the vehicle's maximal carrying capacity. For instance, if an assigned evacuation vehicle can have at most two evacuees, then only two evacuees are always transported to a shelter by the evacuation vehicle, even not one evacuee for the cost saving purpose. This restriction will be needed to grapple with and discussed in more detail in Chapter III.2.2.

The cost function $(f_2(i, j, k, p, t))$ includes both transportation and standby costs of each evacuation vehicle as follows:

$$f_2(i, j, k, p, t) = \sum_{i,j,k,p,t}\left[\xi_k \cdot (\nu_k \cdot 60) \cdot X_{ijkp}^t\right] + \sum_{j,i,k,p,t}\left[\zeta_k \cdot (\nu_k \cdot 60) \cdot Y_{jikp}^t\right] + \sum_{i,k,t}\left(\varphi_i \cdot SV_{ik}^t\right) + \sum_{j,k,t}\left(\rho_k \cdot HV_{jk}^t\right) \quad (3)$$

where ξ_k is the unit cost (*\$/distance*) for transporting evacuees by evacuation vehicle *k*, ζ_k is the unit cost (*\$/distance*) for moving evacuation vehicle *k* without any evacuees, and (φ_i, ρ_k) are the unit costs for managing evacuation vehicles at staging area *i* and at shelter *j*, respectively. The costs (φ_i, ρ_k) are the same regardless of vehicle's types, but the costs (ξ_k, ζ_k) are different according to vehicle's types. ν_k is an average velocity of evacuation vehicle *k*, and the unit is miles per hour (*mph*). The average velocity of each vehicle type is estimated under a normal road condition as considering transportation distance, origin and destination assignment, evacuation vehicles' type and capacity, and evacuees' priorities.

The cost function $(f_3(l, j, p, t))$, related to the practitioners and medical resources, is expressed as follows:

$$f_3(l, j, p, t) = \sum_{l,j,p,t}\left(\varpi_p \cdot Z_{ljp}^t\right) + \sum_{l,p,t}\left(\psi_p \cdot RD_{lp}^t\right) + \sum_{l,p}\left(\vartheta_p \cdot V_{lp}^+ + \phi_p \cdot V_{lp}^-\right) + \sum_{j,p}\left(\chi_p \cdot U_{jp}^+ + \varepsilon_p \cdot U_{jp}^-\right), \quad (4)$$

where ϖ_p is a moving cost of practitioners from their home institution to the shelter.

ψ_p is also the unit cost incurred at an institution for managing a practitioner for treating p-priority patients, the unit costs (ϑ_p, ϕ_p) are the surplus and shortage costs of practitioners at shelters after the whole evacuation process, and similarly, the unit costs (χ_p, ε_p) are the surplus and shortage costs of beds at shelters after the evacuation is completed.

Initial Conditions

$$RP_{ip}^{0} = \lambda_{ip} \qquad \forall i \in I, \forall p \in P \tag{5}$$

$$SV_{ik}^{0} = \begin{cases} 0 & \textit{if not assigned at time } 0 \\ 1 & \textit{if assigned at time } 0 \end{cases} \qquad \forall i \in I, \forall k \in K \tag{6}$$

$$HV_{jk}^{0} = 0 \qquad \forall j \in J, \forall k \in K \tag{7}$$

$$RB_{jp}^{0} = \beta_{jp} \qquad \forall j \in J, \forall p \in P \tag{8}$$

$$RD_{lp}^{0} = \sigma_{lp} \qquad \forall l \in L, \forall p \in P \tag{9}$$

Constraint sets (5)-(9) are initial constraints on the multicorrelated parameters connected with other restrictions. Constraints (5), (8), and (9) indicate the initial number of evacuees at each staging area, beds at each shelter, and practitioners at each institution, respectively. Constraints (6)-(7) show the standby status of each vehicle at staging areas or at shelters at the beginning of disaster evacuation. For example, if there are 30 vehicles available at staging area 1 in the beginning, then $SV_{1k}^{0} = 1, \forall k \in \{1, 2, \cdots, 30\}$, and $SV_{1k}^{0} = 0, \forall k \in \{31, 32, \cdots\}$. This also indicates the starting point of each vehicle is a staging area, and the initial travel time and cost from their origin to a staging area are disregarded.

Staging Area Constraints

$$RP_{ip}^{t+1} = RP_{ip}^{t} - \sum_{j,k} \left(\kappa_{kp} \cdot X_{ijkp}^{t} \right) + \eta_{ip} - \mu_{p} \qquad \forall i \in I,\ \forall p \in P,\ \forall t \in \{0,1,\cdots,ET_{\max}-1\} \tag{10}$$

$$SV_{ik}^{t+1} = SV_{ik}^{t} - \sum_{j,p} X_{ijkp}^{t} + \sum_{j,p} Y_{jikp}^{max\{0,t-\tau_{jik}\}} \qquad \forall i \in I,\ \forall k \in K,\ \forall t \in \{0,1,\cdots,ET_{\max}-1\} \tag{11}$$

Constraint (10) presents the variation of evacuees at each staging area by time. In particular, in the TAT model, we consider the number of each *p*-priority mortality (μ_p) while they waiting for transporting to any shelter. We assume that the highest-priority evacuees may be more likely to die. The number of *p*-priority evacuees (η_{ip}) arrived at staging area *i* from disaster fields are also presented in (10). The priorities of patients are determined during the triage process at the staging area, and can change based on the severity level of injury. However, in this model, the severity level of injury is not improved or aggravated during the evacuation process. In the absence of available vehicles for transporting higher priority evacuees waiting in a staging area, lower priority evacuees can be assigned first if possible.

Constraint (11) indicates the state and location of evacuation vehicles according to their assignment. When considering the number of available evacuation vehicles, τ_{jik} is a specific factor in the model. This is because τ_{jik} is the transportation time between staging area *i* and shelter *j*, which is calculated as $\tau_{jik} = (\delta_{ji} / v_k) \times 60$. In other words, τ_{jik}

depends on the distance (δ_{ji}) between staging area i and shelter j, and average velocity (v_k) of the evacuation vehicle. After starting the evacuation procedure, the evacuation vehicles may be assigned from a staging area to a shelter, and then after τ_{jik} time periods, the evacuation vehicles will arrive at the shelter. They will be able to be reassigned to a staging area again after τ_{jik} time periods. Thus, the number of available vehicles at staging areas is dependent on τ_{jik}, so the assignment of evacuation vehicles can be controlled by τ_{jik}.

If a real-time traffic data is contemplated, then traffic flow conditions of each evacuation route at time t can be factored in the calculation. As per the assumptions of an evacuation vehicle's type and transportation distance, it is possible that there are no vehicles returning from the shelters during the first few time periods. For example, if the length of an arc $(i, j) = (1,1)$ is 50 miles and the average velocity of evacuation vehicle 1 is 50 mph, then evacuation vehicle 1 cannot arrive at staging area 1 back from shelter 1 within 2 hours. In other words, during the first 2 hours of the evacuation period, evacuation vehicle 1 cannot move from shelter 1 to staging area 1 more than once.

Transportation Constraints

$$\sum_{k,p} X_{ijkp}^{t} \le \alpha_{ij} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{12}$$

$$\sum_{k,p} Y_{jikp}^{t} \le \iota_{ji} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{13}$$

The capacity constraint sets (12)-(13) on arc (i, j) ensure that no flow will exist on arc (i, j) if that arc is not a part of the evacuation route. Otherwise, the sum of flow on the arc (i, j) at any time t cannot exceed the arc's capacity α_{ij}, where α_{ij} is the entrance flow leaving staging area i toward shelter j. The reverse is also true for the flow from shelter j to staging area i, represented by ι_{ji}. The flows, α_{ij} and ι_{ji}, may be measured based on historical data and will vary with traffic congestion state of each evacuation route. In other words, the number of evacuation vehicles will increase with the increase in the number of evacuees. The evacuation routes can eventually become congested resulting in no traffic movement. As a result, we need to limit the number of evacuation vehicles entering arc (i, j). α_{ij} and ι_{ji} can be variable over the evacuation time period according to the congestion state of evacuation routes. However, in this thesis, the restricted capacities are fixed after several experiments.

Practitioners Constraints

$$RD_{lp}^{t+1} = RD_{lp}^{t} - \sum_{j} Z_{ljp}^{t} \qquad \forall l \in L, \forall p \in P, \forall t \in \{0,1,\cdots,ET_{\max} - 1\} \tag{14}$$

$$RD_{lp}^{ET_{max}} = V_{lp}^{+} - V_{lp}^{-} \qquad \forall l \in L, \forall p \in P \tag{15}$$

$$\sum_{i,k,t} \left(\kappa_{kp} \cdot X_{ijkp}^{t}\right) \leq \sum_{l,t} \left(\gamma_{p} \cdot Z_{ljp}^{t}\right) \qquad \forall j \in J, \forall p \in P \tag{16}$$

The constraint sets (14)-(16) are general flow restrictions on the practitioners in shelters and their home institutions at time t. The constraints (14) and (15) are the variation and the number of available practitioners in an institution for taking care of patients with multiple priorities, respectively. Constraint (16) presents the minimum number of practitioners required for taking care of patients in each shelter. The ability ratio (γ_p) provides a mechanism in this model to evaluate and match a practitioner's expertise and the number of patients that can be handled by the practitioner. The matching process is beyond the scope of this thesis.

Shelter Constraints

$$HV_{jk}^{t+1} = HV_{jk}^{t} - \sum_{p} Y_{jikp}^{t} + \sum_{p} X_{ijkp}^{max\{0,t-\tau_{ijk}\}} \qquad \forall i \in I, \forall j \in J, \forall k \in K, \forall t \in \{0,1,\cdots,ET_{\max}-1\} \tag{17}$$

$$RB_{jp}^{t+1} = RB_{jp}^{t} - \sum_{i,k} \left(\kappa_{kp} \cdot X_{ijkp}^{t}\right) \qquad \forall j \in J, \forall p \in P, \forall t \in \{0,1,\cdots,ET_{\max}-1\} \tag{18}$$

$$RB_{jp}^{ET_{max}} = U_{jp}^{+} - U_{jp}^{-} \qquad \forall j \in J, \forall p \in P \tag{19}$$

In the shelters, there are some restrictions about evacuation vehicles and medical resources for patients. Constraint (17) addresses standby condition of evacuation vehicles at the shelters. Constraint (18) presents the changing number of beds by time in the shelters, and the number of beds available is controlled according to the number of patients transported at time t, and after the evacuation is completed (ET_{max}). The surplus and shortage cost on the beds after the whole evacuation process are considered in (19).

Integrality, Binary, & Non-negativity Constraints

$$X_{ijkp}^{t}, Y_{jikp}^{t}, SV_{ik}^{t}, HV_{jk}^{t} \in \mathrm{B}, \quad \textit{binary}, \quad \forall i \in I, \forall j \in J, \forall k \in K, \forall p \in P, \forall t \in T \tag{20}$$

$$Z_{ljp}^{t}, RP_{ip}^{t} \in \mathrm{Z}_{+}, \quad \textit{integer}, \quad \forall i \in I, \forall j \in J, \forall l \in L, \forall p \in P, \forall t \in T \tag{21}$$

$$RB_{jp}^{t},\, RD_{lp}^{t} \in \mathrm{Z}, \qquad \textit{integer}, \qquad \forall j \in J,\, \forall l \in L,\, \forall p \in P,\, \forall t \in T \tag{22}$$

$$U_{jp}^{+}, U_{jp}^{-}, V_{lp}^{+}, V_{lp}^{-} \in \Re_{+}, \qquad \forall j \in J,\, \forall l \in L,\, \forall p \in P \tag{23}$$

Finally, constraint sets (20)-(23) have integrality, binary, and non-negativity restrictions. In (22), the decision variables, $\left(RB_{jp}^{t}, RD_{lp}^{t}\right)$, are unrestricted. Considering the mixed-integer decision variables, challenges remain in the trade-offs between the modeling techniques that can accommodate the multifaceted complexity of the evacuation process versus their computational intractability.

III.2.2. Enhanced modeling

In the formal model described in the previous section, there is a restriction on the number of evacuees that can ride each evacuation vehicle. The limitation is relaxed here, so the number of evacuees riding an evacuation vehicle is flexible and is not same as the carrying capacity of the vehicles. In the enhanced model, the number of evacuees for evacuation vehicles to accommodate is a decision variable. It is natural, however, that the number cannot exceed the designated carrying capacity of each evacuation vehicle.

Hence, the objective function is changed to as follows:

$$\textit{Minimize} \quad \sum_{i,j,p,k,t} \left[f_4(i,j,p,k,t) + f_2(i,j,p,k,t) \right] + \sum_{l,j,p,t} f_3(l,j,p,t). \tag{24}$$

The modified partial objective function $\left(f_4(i,j,k,p,t)\right)$ is as follows:

$$f_4(i,j,k,p,t) = \sum_{i,p,t} \left(\varsigma_p \cdot RP_{ip}^{t} \right) + \sum_{i,j,k,p,t} \left(\omega_{kp} \cdot W_{ijkp}^{t} \right), \tag{25}$$

where W_{ijkp}^{t} is the number of p-priority evacuees transported by an evacuation vehicle k on the arc (i, j) at time t. W_{ijkp}^{t} will, in turn, be substituted for $\left(\kappa_{kp} \cdot X_{ijkp}^{t}\right)$.

Hence, constraint sets (10), (16), and (18) are restated as follows:

$$RP_{ip}^{t+1} = RP_{ip}^{t} - \sum_{j,k} W_{ijkp}^{t} + \eta_{ip} - \mu_{p} \qquad \forall i \in I,\ \forall p \in P,\ \forall t \in \{0,1,\cdots,ET_{\max}-1\}, \qquad (26)$$

$$\sum_{i,k,t} W_{ijkp}^{t} \le \sum_{l,t} \left(\gamma_{p} \cdot Z_{ljp}^{t}\right) \qquad \forall j \in J,\ \forall p \in P\ , \qquad (27)$$

$$RB_{jp}^{t+1} = RB_{jp}^{t} - \sum_{i,k} W_{ijkp}^{t} \qquad \forall j \in J,\ \forall p \in P,\ \forall t \in \{0,1,\cdots,ET_{\max}-1\}. \qquad (28)$$

Similar to the primal TAT model, constraint (26) presents the variation of evacuees at staging areas. Constraint (27) guarantees the minimal number of practitioners required for taking care of patients at the shelters. Constraint (28) shows that the number of beds provided from shelters is variable based on the number of evacuees transported by time.

III.3. Numerical experimentation

A numerical experimentation is conducted for natural disaster risk management and operations in order to demonstrate the application of the TAT model. The purpose of the experimentation is twofold: (i) to examine the performance and applicability of the proposed methodology in a LSNDs evacuation network, and (ii) to evaluate the potential merits and deficiencies of implementing resulting optimal evacuation plans in possible evacuation problem instances.

III.3.1. Numerical example

The TAT model is performed on an evacuation network that has 2 staging areas, 3 shelters, 3 institutions, 2 vehicle types (i.e., ambulance and helicopter), and 3 patient-priority types (Fig. 4). In Fig. 4, hospitals indicate the shelters, and institutions refer to the home locations of the practitioners where they normally practice. They are likely to be assigned to one among the shelters during the evacuation process.

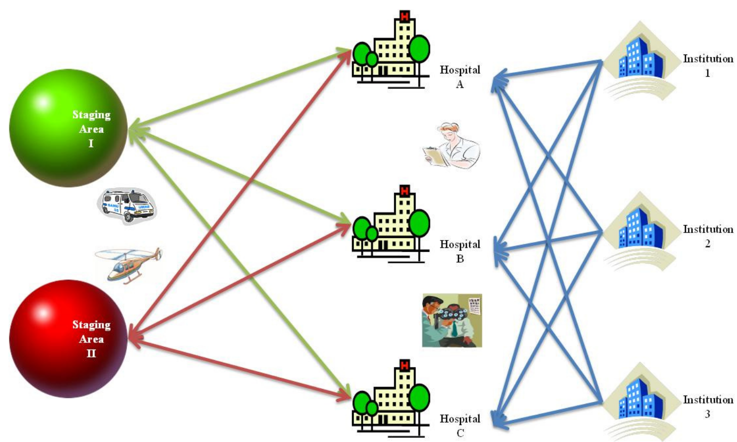

Fig. 4. Illustration of a numerical example

The primal TAT model is discussed first, which is followed by the implementation of the enhanced model. We consider short-notice disasters that have a desirable lead time between 24 and 72 hours. This is because decision makers are required to resolve alternate tactical evacuation strategies based on the expected spatial-temporal influence of the disaster. All of the time period intervals are in 10-minutes increment, and the whole evacuation time is set as 30 hours. Later, several examples with different maximal evacuation time (from 20 hours to 60 hours) are implemented, and their results are compared in order to analyze the issues required for effective disaster evacuation. The velocity of each vehicle is determined based on the assumption of no traffic congestion on the road. For the same vehicle type, the velocities of the evacuation vehicles are assumed to be the same.

In the TAT model, there are two important probability parameters: μ_p and η_{ip}. μ_p indicates an expected number of evacuees that are likely to die at a staging area while waiting for evacuation. The parameter is closely related to the priority of the evacuees. η_{ip} is related to the number of evacuees who arrive from the disaster affected areas into the designated staging areas. Both of the parameters remain the same regardless of staging areas. The parameters of this problem can be generated according to historical data accumulated from several natural disaster occurrences. In this example, the parameters are assumed to follow a Uniform probability distribution, i.e., Uniform [0, 5] for 1st-priority patients. Some parameters related to the initial conditions (5)-(9) are listed in Table 1. λ_{ip} is the number of evacuees at each staging area at the beginning of disaster evacuation. β_{jp} is the number of beds at shelter j for p-priority patients, and σ_{lp} is the number of practitioners at institution l available to provide care for p-priority patients.

Some parameters for evacuation vehicles and network traffic conditions are summarized in Table 2. δ_{ji} is the distance between staging area i and shelter j, and κ_{kp} is the maximal seating capacity of an evacuation vehicle k for p-priority evacuees.

Table 1. Initial conditions

		$p = 1$	$p = 2$	$p = 3$
λ_{ip}	$i = 1$	100	150	200
	$i = 2$	150	250	400
β_{jp}	$j = 1$	500	2000	5000
	$j = 2$	500	3500	5000
	$j = 3$	1000	5000	8500
σ_{lp}	$l = 1$	100	50	30
	$l = 2$	150	75	45
	$l = 3$	200	55	55
		ambulance		*helicopter*
SV_{ik}^{0}	$i = 1$	36		4
	$i = 2$	54		6

Table 2. Parameters for evacuation vehicles and transportation conditions

		$j = 1$	$j = 2$	$j = 3$
φ_i	$i = 1$	5	5	5
	$i = 2$	5	5	5
α_{ij}	$i = 1$	10	15	20
	$i = 2$	5	10	15
ι_{ji}	$i = 1$	10	15	20
	$i = 2$	5	10	15
δ_{ij}	$i = 1$	15	20	30
	$i = 2$	10	15	20
		ambulance		*helicopter*
ζ_k		1		3
(ξ_k, ρ_k)		(2, 5)		(5, 5)
ν_k		60		100
κ_{kp}	$p = 1$	1		2
	$p = 2$	2		5
	$p = 3$	3		10

An empty evacuation vehicle moving from a shelter to a staging area is assumed to have a lower transportation cost. In other words, the unit cost while transporting an evacuee is higher. The unit cost (ς_p) for transportation is shown in Table 3.

Table 3. Parameters for evacuees

		p = 1	*p = 2*	*p = 3*
ς_p (*$/evacuee/min*)		150	50	20
ω_{kp}	*ambulance*	20	10	5
	helicopter	30	15	7

The *1st*-priority patients have a higher cost than lower-priority patients. This implies that patients with the highest-priority must be transported first, which will satisfy the aim of the objective function to minimize total evacuation cost. ω_{kp} is the unit cost for taking care of a *p*-priority evacuee during transportation by evacuation vehicle *k* (*$/evacuee*). The parameter is determined based on the evacuation vehicle's type and the priority of evacuees.

III.3.2. Results and analysis

These problem instances were solved using IBM OPL IDE 6.3, ILOG CPLEX 12.1.0 software on a Dell OPTIPLEX 960 with two 3.00 GHz CPU Intel® Core™2 Quad processors and 8 GB RAM. The primary results are shown in Table 4. The example model contains 548,843 constraints, 330,687 integer variables, 742,100 binary variables, and 4,380 real variables.

Table 4. Computation primary results

	TAT	LP relaxation
Total Cost	$12M	$7M
# of evacuees	997	846
# of practitioners	683	579
CPU time	86,197 sec	6,028 sec
Iterations	20,968,315	1,209,457

The B&C algorithm is applied to obtain an exact solution to the problem. In most cases, the B&C algorithm is able to solve and prove optimality for large-scale problems compared to the cutting-plane method or the branch-and-bound algorithm (Kumar *et al.*, 2010). It took about 86,197 seconds to obtain the optimal solution. The objective function value is $12M, and this is selected among 21 solution pools. The integer optimal solution was obtained after 20,968,315 iterations with 4,753 nodes.

The objective cost ($11.96M) is close to the incumbent objective cost ($11.97M) obtained after about 7,200 seconds. One of the available options for solving large-scale problems in polynomial time would be to decide on a reasonable gap between the desired goal and the incumbent objective cost. Using such an approach, it is possible to scale up the evacuation model reflecting the realities of the disaster compared to other approaches such as decomposition methodologies or heuristic approaches.

The objective value ($M) and gap (%) obtained at each iteration are illustrated in Fig. 5. The MIP gap is the difference between the best integer solution and the objective of the best node remaining, after which the B&C algorithm is stopped and a feasible solution is begun searching. It can be seen that the interim solution after about 2,000 seconds has a significantly smaller gap, compared to the initial difference.

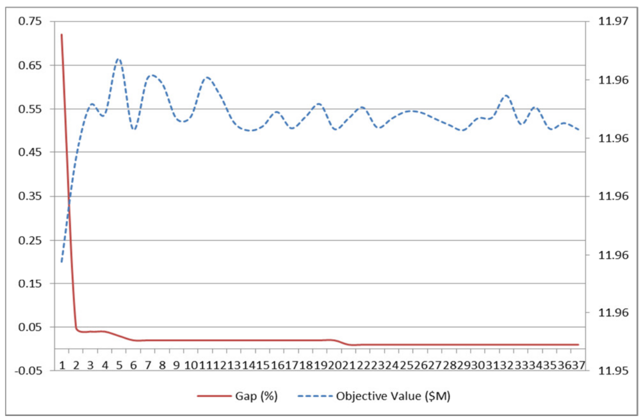

Fig. 5. Objective value ($M) and gap (%)

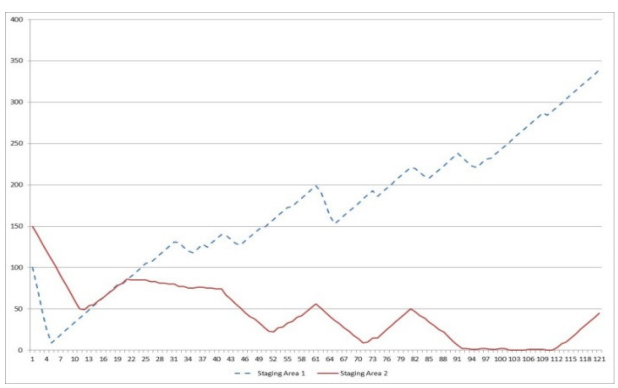

Fig. 6. Trend of number of 1st-priority patients remaining in both staging areas

Fig. 6 highlights a few other implications. Staging area *1* requires more evacuation vehicles and medical practitioners. This is because the number of evacuees waiting in staging area *1* is increasing as the evacuation progresses. On the other hand, staging area *2* has enough medical resources for evacuating *1*st-priority patients under current conditions, as you can see in Fig. 6.

Fig. 7 shows the assignment and allocation example of evacuation vehicles between staging areas and shelters. The top points represent the state of evacuation vehicles transported *p*-priority evacuees from staging area *1* to shelter *A*. The middle points show that the evacuation vehicles staying at shelter *A* return to staging area *1*. The differences between the top and middle points indicate the effectiveness on the assignment and allocation of the evacuation vehicle.

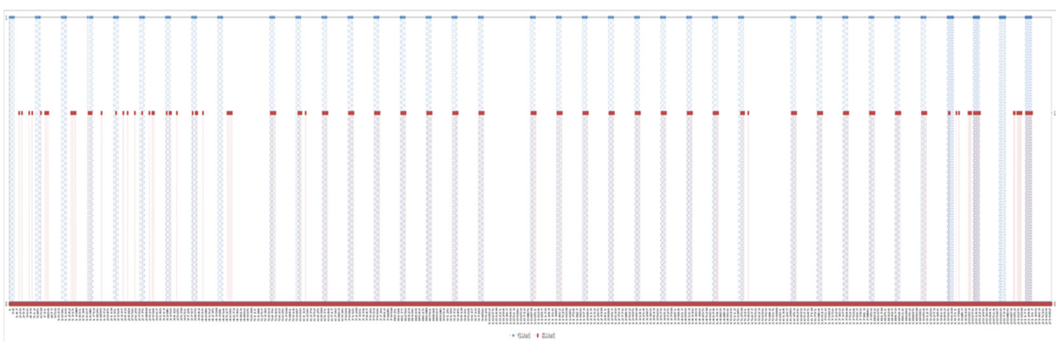

Fig. 7. Example of evacuation vehicle assignment for *p*-priority evacuees on arc *(1*, *A)*

Although it is trivial that LP relaxation results are lower than the TAT model's, we check to see how the results of the TAT model increase in comparison with the LP relaxation model. Several interesting results are observed (Table 4), when comparing the linear programming model. For total cost, the TAT model has a higher cost (Δ71%) than the LP model, which was as expected. For the number of evacuees, there is a 17.85% increase in the TAT model. Even with the increase in the evacuation cost for a natural disaster, the number of survivals increases slightly. Thus, the number of evacuees transported by each evacuation vehicle needs to be flexible under their maximum capacity, instead of the assumption that the number of evacuees that can be transported by each evacuation vehicle is fixed.

Considering the models with several scenarios, 9 different scenarios are resolved and compared (Table 5). The problems have different maximal evacuation time from 20 hours (TAT-120T) to 60 hours (TAT-360T), including the enhanced TAT model (eTAT-180T). CPLEX 12.1.0 is used to solve the MILP formulation of this problem. CPLEX runs are stopped after 7200 CPU seconds, and the best solutions under the restriction are reported. As the whole evacuation time is increasing in each scenario, the MIP bound gap with the best lower bound at each problem is mounting slowly (Table 5).

Reviewing the results of these experiments with various scenarios, we show that every experiment can have reasonable local optimum solutions within the pre-specified CPU solution time (Fig. 8). We observe that the results are not influenced by the CPU solution time. In other words, although a large-scale problem is solved with a large CPU solution time, it is not remarkably different with the situations with shorter solution time. Thus, if we solve the disaster evacuation problems using the TAT model and can set up a restricted error range, then we can find a local optimal solution within polynomial time (e.g., all experiments except TAT-180T-2 and eTAT-180T), instead of solving the problems until a global optimal value (e.g., TAT-180T-2 experiment) is obtained. These can carry an important meaning that leads to the reduction of solution time and evacuation total cost.

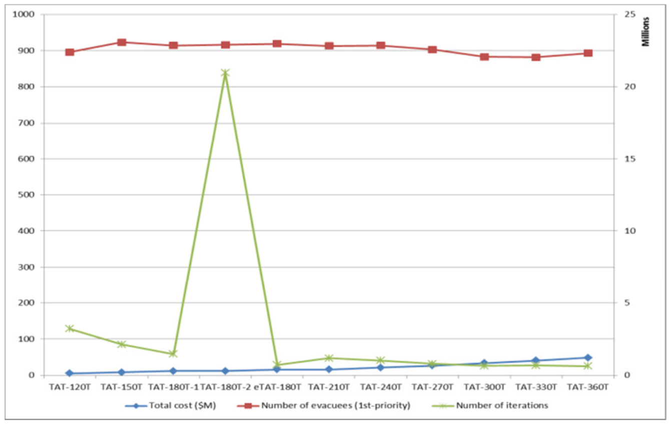

Fig. 8. Results comparison of the 10 scenarios

The two scenarios, TAT-180T-1 and TAT-180T-2, have different CPU time for solving the same problem. TAT-180T-1 needed 7,200 seconds for obtaining a solution. There was no time limit set for TAT-180T-2, and it stopped after 86,404 seconds.

However, there is not a significant difference of total cost when compared to TAT-180T-1. Although we have enough time to solve a large-scale problem, it does not lead to a significantly improved total cost when compared to the case with a shorter solution time. When this model is applied to solve a real-life problem with the large-scale number of staging areas, shelters and evacuation vehicles, the convergence may be slow. The problem size and solution time can pose significant challenges in obtaining the optimal solution. One of the possible options is to solve the enhanced model. The scenario, eTAT-180T in Table 5, is related to the enhanced model. The experiment shows that if the evacuation vehicles have flexibility in the number of patients to be transported, it can result in an improved objective cost. However, the gap between the optimal objective value and the interim objective increases. This is a trade-off for the decision makers.

Table 5. Comparison of results for each TAT model

Problem	Total Cost ($M)	MIP Bound (Gap, %)	# of Evacuees (for 1st priority)	CPU Time (second)	# of Iterations
TAT-120T	5.59	0.07	896	7,201.90	3,219,313
TAT-150T	8.40	0.07	923	7,206.73	2,136,509
TAT-180T-1	11.97	0.12	914	7,205.86	1,464,598
TAT-180T-2	11.96	0.02	916	85,917.02	20,968,315
eTAT-180T	16.49	1.08	919	7,201.26	729,824
TAT-210T	16.27	0.09	913	7,207.36	1,188,886
TAT-240T	21.31	0.14	914	10,804.65	1,021,839
TAT-270T	27.13	0.27	903	7,201.99	803,335
TAT-300T	33.81	0.69	883	7,207.73	662,669
TAT-330T	41.11	0.66	882	7,203.52	693,418
TAT-360T	49.04	0.41	893	7,204.73	636,079

III.4. Summary and conclusion

Developing a timely and effective disaster evacuation model is one of the key strategies of saving lives during a natural disaster. The decision-making capability of the model can provide a mechanism for improving disaster response planning. In Chapter III, we provide an overview of the evacuation network models for LSNDs and consider a disaster evacuation model using an MILP. The model decides on the tactical routing assignment of multiple types of evacuation vehicles in order to transport evacuees with various priorities from affected areas to safe shelters. The TAT model is a MILP and minimum-cost flow problem. Comprehensive computational experiments are performed to examine the applicability and extensibility of the TAT model.

The main contribution of TAT model is that it proposes a large-scale deterministic network evacuation model to allow the use of an exact solution approach, such as B&C method, for solving the MILP problem. Another contribution is that we show the quality of solutions remained very close to the optimal value even if the whole evacuation time is subject to small changes. For an effective solution approach, several scenarios with different assumptions and parameters are analyzed and compared, followed by a discussion of some of the interesting observations in the scenarios. In particular, we show that the B&C procedure can yield reasonable solutions in polynomial computation time by solving large-scale problems with the proposed formulation. Consequently, the proposed model enables decision-makers to design a useful evacuation strategy with some conditions such as a type or severity level of a natural disaster, affected area information, or an emergency measure in the preparedness stage. This will enhance rapid response performance of LSNDs management authorities.

In addition, this study not only proposes a model that can be incorporated into any such decision-support tool, but also reveals the value of information on instances as the whole evacuation time is changed. In some instances where the whole evacuation time is greater than 60 hours, difficulties have been observed resulting in an explosion in the search tree. In disaster risk management, challenges remain in the trade-offs between the realism of the models that can accommodate the multifaceted complexity of the evacuation process versus their computational intractability.

The TAT model can offer insight to decision makers about the number of staging areas, evacuation vehicles, and medical resources that are required to complete a large-scale evacuation based on the estimated number of evacuees. We also expect that the TAT model can be applied to several research areas such as Transportation, Logistics, or even Manufacturing.

CHAPTER IV

LARGE-SCALE EVACUATION NETWORK MODEL FOR TRANSPORTING EVACUEES WITH MULTIPLE PRIORITIES

IV.1. Introduction

The extent of cumulative damage by recent LSNDs is too extreme to be estimated. Over the past few years, the growth rate of victims affected by LSNDs has decreased steadily, but the estimated damage cost has increased rapidly (Na and Banerjee, 2012). With ever increasing damage being caused by LSNDs, the need for appropriate evacuation strategies has grown dramatically. Evacuation decision-makers face numerous challenges when determining how to transport evacuees efficiently, find the best evacuation routes from affected areas to safe shelters, and distribute indispensable medical resources to the right shelter at the right time.

Within the context of the proposed MILP model, we make the following contributions. First, this model suggests a disaster evacuation network modeling technique that allows the optimal shelters' number and location, evacuation routes assignment, evacuation vehicles allocation, and distribution of medical resources. Second, our proposed solution framework can solve a LSND evacuation problem considering critical spatial-temporal conditions. Finally, the proposed modeling methodology can be integrated with either simulation-based or (meta) heuristics-based methods, which means that the this research is applicable to a wide range of models and tools that are familiar to researchers in industrial engineering, transportation engineering, or computer science.

IV.2. Problem description

A MILP problem is described for coping with LSND with a complicated evacuation network. Initially, evacuees are taken to staging areas immediately when they are found, then their priorities are determined by a triage system, and emergency treatments are provided based on their severity level. Staging areas must be spacious areas located around disaster fields and accessible by evacuation vehicles.

Shelters are temporary medical facilities that can be used to house evacuees during the period of evacuation. There are three possible types of shelters: extensive shelters, restricted shelters, and other large shelters without medical infrastructure. Extensive shelters (e.g., hospital) are large medical facilities that have existing capabilities to provide care for the various priorities of evacuees. However, the capacity of extensive shelters in an affected region is often limited. Restricted shelters (e.g., clinic, medical center) are smaller medical facilities than extensive shelters, and have existing capabilities to provide treatment for evacuees. The number of restricted shelters in an affected region is expected to be higher than the number of extensive shelters, but restricted shelters are also limited. Other large shelters without medical infrastructure (e.g., sports arena, theater) are extensive facilities that can accommodate a large number of evacuees with suitable amounts of basic amenities such as climate control, bathrooms, kitchen, and sufficient space to organize beds. Such facilities do not have the inherent capabilities to take care of the various priorities of evacuees. The restricted shelters and other large shelters without medical infrastructure are called candidate shelters, which can be transformed into evacuation shelters during a period of evacuation only.

After determining the number and location of shelters, decision-makers have to decide the type and number of evacuation vehicles and find optimal evacuation routes to satisfy their objectives. Each evacuation vehicle has different capacities, transportation costs, and average velocities. With transporting evacuees to assigned shelters, there are also logistics flows of medical resources shipped from relief warehouses to the right shelter at the right time. Next, we proceed with a discussion on the mathematical modeling of the problem of interest. For this purpose, in Fig. 9, we first present the underlying structure of the proposed evacuation model including the location sets along with the flow and some notable decision variables.

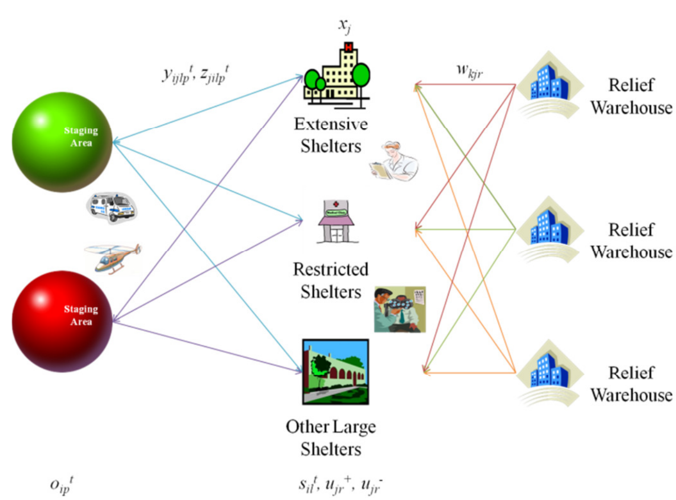

Fig. 9. Underlying structure of the proposed model network

IV.3. Mathematical modeling

Herein, we formulate the tactical evacuation planning problem as a MILP for LSNDs. The objective is to minimize the total evacuation cost and to maximize the number of survivors simultaneously. For an effective response phase of a natural disaster, the proposed model finds the number and location of shelters and a strategy on the routing assignment of evacuation vehicles. In order to provide evacuees with indispensable medical resources efficiently, our model also addresses amounts of initial holding stocks and the way to distribute medical resources. The proposed model takes into account the severity levels of evacuees in each staging area, the capacities of evacuation vehicles and routes, and available medical resources in every shelter.

In the proposed model, strategic assumptions are as follows:

- Associated costs are explained in five categories: (i) setup costs, which transform candidate shelters into formal evacuation shelters, (ii) care costs when evacuees are waiting for transportation to shelters and while evacuees are transported by evacuation vehicles, (iii) holding costs of medical resources in each shelter and evacuation vehicles in each staging area, (iv) transportation costs, which arise from transporting evacuees from staging areas to shelters and shipping medical resources from relief warehouses to shelters, and (v) surplus and shortage costs of medical resources per unit time. All costs are determined or changed by the priorities of evacuees, the types of evacuation vehicles, and the types of medical resources.

- All evacuation vehicles are located in the staging areas at the beginning of the evacuation process. When the evacuation vehicles depart from a staging area, they can transport evacuees to any shelter considering the relevant constraints, but have to return from the assigned shelter to the initial staging area.
- The medical resources used for the period of evacuation are expensive, but are always in demand and consumed on a regular basis. On the other hand, maintaining many of the medical resources at every potential candidate shelter is inefficient and not cost-effective. Every shelter can have initial or safe stocks in order to mitigate the difficulties in mobilization of medical resources during the period of evacuation, but a holding cost is incurred. The shipping and holding costs are different according to the classification of medical resources and the distance between relief warehouses and shelters.

IV.3.1 Sets and indices

I Set of staging areas; $\forall i \in I = \{1, 2, \cdots, SA_{\max}\}$

J Set of shelters; $\forall j \in J = \{1, 2, \cdots, SH_{\max}\}$, $J = J_E \cup J_C$

J_E Set of extensive shelters;

J_C Set of candidate shelters; $J_C = J_R \cup J_O$

J_R Set of restricted shelters;

J_O Set of other large shelters without medical infrastructure

K	Set of relief warehouses; $\forall k \in K = \{1, 2, \cdots, RW_{\max}\}$
L	Set of evacuation vehicles; $\forall k \in K = \{1, 2, \cdots, VH_{\max}\}$
P	Set of evacuees priorities; $\forall p \in P = \{1, 2, \cdots, EP_{\max}\}$
R	Set of medical resources; $\forall r \in R = \{1, 2, \cdots, MR_{\max}\}$
T	Set of evacuation periods; $\forall t \in T = \{0, 1, \cdots, ET_{\max}\}$

IV.3.2 Parameters

κ_j	Setup cost for transforming candidate shelter $j (\in J_C)$ into a formal evacuation shelter
ξ_p	Unit cost for taking care of *p*-priority evacuees in staging areas *($/evacuee/minute)*
θ_l	Unit cost for holding an evacuation vehicle *l* in staging areas *($/minute)*
τ_{ijl}	Transportation time of evacuation vehicle *l* from staging area *i* to shelter *j*
ζ_l	Unit cost of evacuation vehicle *l* for transporting evacuees *($/distance)*
δ_{ijl}	Actual distance of arc (*i, j)* for evacuation vehicle *l (mile)*
v_l	Average velocity of evacuation vehicle *l (mph)*
h_r	Unit cost for holding *r*-type medical resources in a shelter before occurring a natural disaster *($/resource)*

σ_r Unit cost for shipping r-type medical resources to shelters *($/resource/distance)*

δ_{kj} Actual distance of arc *(k, j) (mile)*

φ_r^+ Surplus cost of r-type medical resources *($/resource)*

φ_r^- Shortage cost of r-type medical resources *($/resource)*

ϑ_{kr} Maximal capacity of r-type medical resources in relief warehouse k

ρ_{jp} Maximal capacity of p-priority evacuees that shelter j can be accommodated

η_{ip} Number of p-priority evacuees in staging area i at the beginning of evacuation processes

ϖ_{lp} Maximal number of p-priority evacuees who can be accommodated on evacuation vehicle l

ψ_{ijl}^t Maximal number of evacuation vehicle l that can pass on a route *(i, j)* at time t

χ_l Preparation time of evacuation vehicle l for transporting next evacuees

IV.3.3 Decision variables

x_j = 1, if candidate shelter $j(\in J_C)$ is selected as an evacuation shelter;

= 0, otherwise

y_{ijlp}^t Number of p-priority evacuees transported by evacuation vehicle l through arc $(i \rightarrow j)$ at time t

z_{ijlp}^t = 1, if evacuation vehicle l transported p-priority evacuees through arc $(i \rightarrow j)$ at time t; = 0, otherwise

o_{ip}^t Number of p-priority evacuees remaining in staging area i at time t

s_{il}^t Number of evacuation vehicle l preparing to transport evacuees in staging area i at time t

w_{kjr}^t Amount of medical resources r shipped through arc $(k \rightarrow j)$ at time t

u_{jr} Amount of medical resources r required to be prepared in shelter j at the beginning of evacuation processes

q_{jr}^{t+} Surplus amount of r-type medical resources remained at shelter j at time t

q_{jr}^{t-} Shortage amount of r-type medical resources remained at shelter j at time t

IV.3.4 Objective function

$$\begin{aligned}
\textit{Minimize} \quad & \sum_{j \in J_C} \left(\kappa_j \cdot x_j \right) + \sum_{i \in I} \sum_{p \in P} \sum_{t \in T} \left(\xi_p \cdot o_{ip}^t \right) + \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} \left(\theta_l \cdot s_{il}^t \right) \\
& + \sum_{i \in I} \sum_{j \in J} \sum_{l \in L} \sum_{p \in P} \sum_{t \in T} \left(\xi_p \cdot \tau_{ijl} \cdot y_{ijlp}^t + 2 \cdot \zeta_l \cdot \delta_{ijl} \cdot z_{ijlp}^t \right) \\
& + \sum_{j \in J} \sum_{r \in R} \left(h_r \cdot u_{jr} \right) + \sum_{k \in K} \sum_{j \in J} \sum_{r \in R} \sum_{t \in T} \left(\sigma_r \cdot \delta_{kj} \cdot w_{kjr}^t \right) + \sum_{j \in J} \sum_{r \in R} \sum_{t \in T} \left(\varphi_r^+ \cdot q_{jr}^{t+} + \varphi_r^- \cdot q_{jr}^{t-} \right)
\end{aligned} \tag{29}$$

There is a setup cost for transforming a candidate shelter into a formal evacuation shelter. The restricted shelters have a somewhat lower setup cost than the other large shelters without medical infrastructure. The care costs are incurred in every staging area and during transportation to shelters, which is determined by evacuees' priority, distance between staging areas and shelters, and evacuation vehicles' type. Note that the medical cost for evacuees with the highest priority is the most expensive.

When evacuation vehicles are waiting to transport evacuees, the holding cost is determined based on the waiting time and evacuation vehicle's type. The transportation cost of evacuation vehicles is calculated by the transportation distance and the evacuation vehicle's type. Although we consider a distance on the same set of a staging area and a shelter, the distance is different by the evacuation vehicle's type. For instance, a helicopter moves a shorter distance from a staging area to a shelter than an ambulance. If medical resources in each shelter are higher or lower than the required amounts, surplus or shortage costs are incurred each time.

IV.3.5 Constraints

$$\sum_{j \in J_C} \left(\rho_{jp} \cdot x_j \right) \geq \sum_{i \in I} \eta_{ip} - \sum_{j \in J_E} \rho_{jp}, \quad \forall p \in P \tag{30}$$

$$\sum_{j \in J} \sum_{l \in L} \sum_{t \in T} y_{ijlp}^{t} \leq \eta_{ip}, \quad \forall i \in I, \forall p \in P \tag{31}$$

$$\sum_{i \in I} \sum_{l \in L} \sum_{t \in T} y_{ijlp}^{t} \leq \rho_{jp} \cdot \left(1_{j \in J_E} + x_j \cdot 1_{j \in J_C} \right), \quad \forall j \in J, \forall p \in P \tag{32}$$

$$y_{ijlp}^{t} \leq \varpi_{lp} \cdot z_{ijlp}^{t} \cdot \left(1_{j \in J_E} + x_j \cdot 1_{j \in J_C} \right), \quad \forall i \in I, \forall j \in J, \forall l \in L, \forall p \in P, \forall t \in T \tag{33}$$

$$o_{ip}^{t} = o_{ip}^{t-1} - \sum_{j\in J}\sum_{l\in L} y_{ijlp}^{t}, \quad \forall i \in I, \forall p \in P, \forall t \in T \setminus \{0\} \tag{34}$$

$$\sum_{p\in P}\sum_{t'=t-\tau_{ijl}+1}^{t} z_{ijlp}^{t'} \le \psi_{ijl}^{t} \cdot \left(1_{j\in J_E} + x_j \cdot 1_{j\in J_C}\right), \quad \forall i \in I, \forall j \in J, \forall l \in L, \forall t \in T \tag{35}$$

$$s_{il}^{t} = s_{il}^{t-1} - \sum_{j\in J}\sum_{p\in P} z_{ijlp}^{t} + \sum_{j\in J}\sum_{p\in P} z_{ijlp}^{\max\{0,t-2\cdot(\tau_{ijl}+\chi_l)\}}, \quad \forall i \in I, \forall l \in L, \forall t \in T \setminus \{0\} \tag{36}$$

$$\sum_{j\in J}\sum_{t\in T} w_{kjr}^{t} \le \vartheta_{kr}, \quad \forall k \in K, \forall r \in R \tag{37}$$

$$u_{jr} + \sum_{k\in K} w_{kjr}^{t} - \sum_{i\in I}\sum_{l\in L}\sum_{p\in P} y_{ijlp}^{t-\tau_{ijl}} = q_{jr}^{t+} - q_{jr}^{t-}, \quad \forall j \in J, \forall r \in R, \forall t \in T \setminus \{0\} \tag{38}$$

$$x_j, z_{ijlp}^{t} \in B, \quad \forall i \in I \tag{39}$$

$$y_{ijlp}^{t}, o_{ip}^{t}, s_{il}^{t} \ge 0, \quad \forall i \in I, \forall j \in J, \forall l \in L, \forall p \in P, \forall t \in T \tag{40}$$

$$w_{kjr}^{t}, u_{jr}, q_{jr}^{t+}, q_{jr}^{t-} \ge 0, \quad \forall j \in J, \forall k \in K, \forall r \in R, \forall t \in T \tag{41}$$

Constraint (30) ensures that the total capacity (ρ_{jp}) of existing extensive shelters and new selected candidate shelters cannot be less than the total number of evacuees in all staging areas at the beginning of the evacuation process. Constraint (31) states that the total number of *p*-priority evacuees transported from staging area *i* to any shelters is less than or equal to the number of *p*-priority evacuees in each staging area at the beginning of the evacuation process. At the same time, constraint (32) guarantees that the total number of *p*-priority evacuees transported to each assigned shelter *j* cannot exceed the maximal capacity of formal evacuation shelters. Note that $1_{j\in J_E}$ (or $1_{j\in J_C}$) is an indicator function having the value 1 for all elements in J_E (or J_C) and the value 0 for all elements not in J_E (or J_C). In addition, the capacity constraint (32) on arc *(i, j)* ensures that no flow will exist on arc *(i, j)* if that arc is not a part of the evacuation route. When evacuees are rushed by evacuation vehicles to shelters, the maximal capacity of evacuation vehicles is also considered. Constraint (33) indicates that the number of evacuees transported to assigned shelters at a time cannot exceed the sum of the maximal capacity of evacuation vehicles based on the evacuee priority and the evacuation vehicle type. Constraint (34) represents the variation in evacuees of each staging area, and in this model, we consider no additional evacuees generated from disaster fields and no fatalities during the whole evacuation period. If the evacuees occur from disaster fields to staging areas during evacuation processes, we can consider a probability model based on previous existing historical data. Note that no evacuees are transported from staging areas to shelters at the beginning of the evacuation process, that is $y_{ijlp}^0 = 0$.

Constraint (35) addresses the maximal capacity (ψ_{ijl}^t) of evacuation routes, which is involved with the number of road traffic lanes, condition of assigned roads, type of evacuation vehicles, and observation time slots. The evacuation vehicles occupy the road during τ_{ijl} minutes under a normal scenario. The total number of evacuation vehicles on the arc *(i, j)* from $t - \tau_{ijl} + 1$ to t, therefore, cannot exceed the maximal capacity of the road. τ_{ijl} is the transportation time of evacuation vehicle *l* under normal traffic conditions between staging area *i* and shelter *j*, which is calculated as $\tau_{ijl} = (\delta_{ijl} / v_l) \times 60$. After launching the evacuation procedure, the evacuation vehicles may be allocated from a staging area to a shelter, and then after τ_{ijl} minutes, the evacuation vehicles will arrive at the assigned shelter. They will be able to be reassigned to a staging area again after ($\tau_{ijl} + \chi_l$) minutes. As per the assumptions of an evacuation vehicle's type and transportation distance, it is possible that there are no evacuation vehicles returning from shelters during the first few periods. Thus, the number of available evacuation vehicles in staging areas is dependent on τ_{ijl}, so the assignment of evacuation vehicles can be controlled by τ_{ijl}. Note that no evacuation vehicles move from staging areas to shelters at $t = 0$, that is $z_{ijlp}^0 = 0$.

Constraint (36) is related to the state and location of evacuation vehicles according to their assignment, and manages the allocation of evacuation vehicles to evacuees or shelters. If an evacuation vehicle has a traffic time (τ_{ijl}) between staging area i and shelter j under normal traffic conditions and preparation time (χ_l) of the evacuation vehicle for transporting next evacuees, the evacuation vehicle can arrive at its initial staging area i again after $2 \cdot \tau_{ijl} + \chi_l$ minutes. Constraint (36) also states that the number of evacuation vehicles l for transporting p-priority evacuees from shelter j to staging area i is none from beginning to $2 \cdot \tau_{ijl} + \chi_l$. Note that the initial number of evacuation vehicles in each staging area is determined before starting the evacuation processes. For example, let us suppose there are 50 ambulances and 10 helicopters in staging area 1 and 30 ambulances and 5 helicopter in staging area 2. Then for *l=1..60*, $s_{1l}^0 = 1$, but for *l=61..95*, $s_{1l}^0 = 0$. Conversely, for *l=1..60*, $s_{2l}^0 = 0$, but for *l=61..95*, $s_{2l}^0 = 1$

. But if a candidate shelter is not selected as an evacuation shelter, the evacuation vehicles are not assigned at the candidate shelter. This also indicates that the starting point of each evacuation vehicle is a staging area, and the initial travel time and cost from their origin to a staging area are disregarded.

Constraint (37) restricts the amount of medical resources shipped from relief warehouses to shelters by the volume of each type of medical resources kept in each relief warehouse. Constraint (38) decides the initial amount of medical resources required to minimize the costs for distributing and mobilizing medical resources to shelters. In this model, we have assumed that an evacuee requires an l-type medical resource to be treated. In particular, when surplus or shortage of medical resources arises, the relevant costs are incurred per unit time.

Constraint (39) enforces the integrality restrictions on the binary variables and finally constraints (40-41) enforce the non-negativity restrictions on the corresponding decision variables.

IV.4. Solution approach

Due to the large number of variables and constraints involved in the proposed model, direct use of traditional and standard solvers is found to be highly inefficient. The BD approach, specifically, has proven to be a powerful technique for solving such large-scale MILP problems. This section describes our solution framework including a modified BD based on GIS in order to solve a LSND evacuation problem.

The overall solution framework is illustrated in Fig. 10. First, the GIS module computes the shortest paths from staging areas to candidate shelters if the candidate shelters are within a reasonable and specified transportation time and/or distance, as accommodating all evacuees. With multiple staging areas and multiple candidate shelters, the GIS module utilizes the Dijkstra's algorithm and generates candidate evacuation shelters ($J = J_E \cup J_C$) where can be used in an experiment. The GIS module also provides the potential evacuation routes between staging areas and the selected candidate evacuation shelters ($J = J_E \cup J_C$) as well as the relevant routes' information. The ArcGIS network analyst extension makes the evacuation route network to obtain an initial incumbent solution of the master problem.

Then, with the initial solution obtained from the GIS module, the modified BD algorithm starts to solve the problem. The optimal number and location of evacuation shelters are determined, and evacuation vehicles are allocated and assigned by the evacuation plan. Concurrently, the algorithm finds an efficient logistics plan for shipping medical resources to shelters. The GIS component is based on ArcGIS 10.1.

The BD algorithm is applied iteratively over the relaxed master and subproblems until convergence is achieved. The convergence criterion is satisfied when $(UB - LB) \le (\varepsilon \cdot |UB|)$, where *UB* is an upper bound obtained by the best optimal solution of the subproblem and the dual-problem, *LB* is a lower bound by the solution of the last master problem, and ε is the tolerance for stopping criterion and is extremely small in value. This procedure is summarized in step 4 of the modified BD algorithm, which is described as follows.

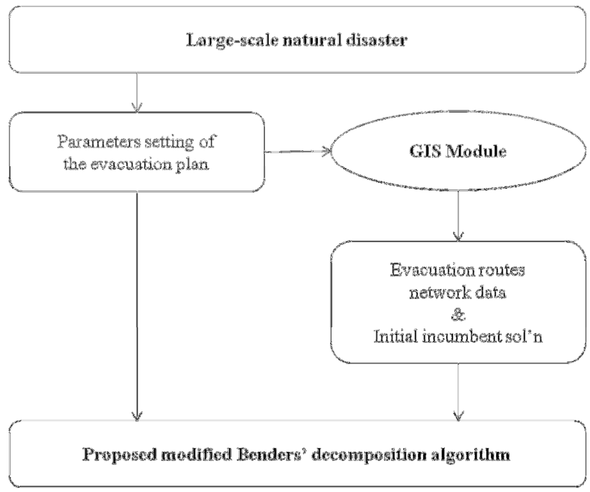

Fig. 10. Solution framework

Step 1: (*Initialization*)

Initialize the iteration counter n, the LB l of the objective function, and its UB u. The initial solution set, $X_0 = \left\{ x_j^{\,0}, y_{ijlp}^{t\;0}, z_{ijlp}^{t\;0}, o_{ip}^{t\;0}, s_{il}^{t\;0} \right\}$, is obtained by the GIS Module.

Step 2: (*Solve subproblem*)

Solve the subproblem as follows:

$$f^* = Min\left\{ \sum_{j\in J}\sum_{r\in R}\left(h_r \cdot u_{jr}\right) + \sum_{k\in K}\sum_{j\in J}\sum_{r\in R}\sum_{t\in T}\left(\sigma_r \cdot \delta_{kj} \cdot w_{kjr}^t\right) + \sum_{j\in J}\sum_{r\in R}\sum_{t\in T}\left(\varphi_r^+ \cdot q_{jr}^{t+} + \varphi_r^- \cdot q_{jr}^{t-}\right) \mid s.t.\ (9),(10),(13) \right\}.$$

If feasible, generate an optimality cut [2].

Compute the UB:

$$v^* \leftarrow \sum_{j\in J_C}\left(\kappa_j \cdot x_j\right) + \sum_{i\in I}\sum_{p\in P}\sum_{t\in T}\left(\xi_p \cdot o_{ip}^t\right) + \sum_{i\in I}\sum_{l\in L}\sum_{t\in T}\left(\theta_l \cdot s_{il}^t\right) + \sum_{i\in I}\sum_{j\in J}\sum_{l\in L}\sum_{p\in P}\sum_{t\in T}\left(\xi_p \cdot \tau_{ijl} \cdot y_{ijlp}^t + 2 \cdot \zeta_l \cdot \delta_{ijl} \cdot z_{ijlp}^t\right) + f^*$$

$$u \leftarrow Min\left\{v^*, u\right\}.$$

If u is updated, set incumbent solution set:

$$X^{*} = \left\{x_j^{\;n}, y_{ijlp}^{t\;\;n}, z_{ijlp}^{t\;\;n}, o_{ip}^{t\;n}, s_{il}^{t\;n}\right\}$$

else if infeasible, generate a feasibility cut [2].

Step 3: (*Add cut to MP and solve it*)

If subproblem was feasible,

Add an optimality cut to MP.

else

Add a feasibility cut to MP.

Solve MP to get X^{n+1} and v^{n+1} as the optimal value.

Set $l \leftarrow Max\left\{v^{n+1}, l\right\}$.

Step 4: (*Termination*)

Check the difference between UB and LB.

If $(UB - LB) \leq (\varepsilon \cdot |UB|)$, stop.

else

Set $n \leftarrow n+1$.

Return to Step 2.

IV.5. Computational experiments

A numerical experiment is conducted for a LSND evacuation problem. The purpose of the experiment is twofold: (i) to explore the applicability and performance of the proposed model in a large-scale evacuation network, and (ii) to evaluate the potential merits and deficiencies of implementing resulting optimized evacuation plans in a possible LSND problem instance.

The proposed model is performed on a LSND evacuation network that has 2 staging areas, 2 existing shelters, 6 candidate shelters, 2 relief warehouses, 80 evacuation vehicles, 3 patient-priority types, 2 evacuation vehicle types, and 3 medical resource types. In particular, 6 candidate shelters are classified as 3 restricted shelters and 3 other large shelters without medical infrastructure in the network. The city of Galveston, Texas is used as an example for designing the LSND evacuation network. The city is about 45 miles southeast of downtown Houston. The Galveston causeway is the only major road connected to neighborhood areas. If the Galveston causeway is rendered unusable by a LSND, there are few routes to transport evacuees to nearby areas. Given these characteristics of the city of Galveston, it is necessary to establish an evacuation strategy against LSNDs.

In the experiment, we consider a short-notice natural disaster that has a desirable lead time of around 24 hours. This is because decision-makers are required to develop alternate tactical evacuation strategies based on the expected spatial-temporal influence of impending natural disasters. If necessary, decision-makers can establish an alternate evacuation plan every 24 hours approximately. All of the time period intervals are in 1-minute increments, and the whole evacuation time (*ETmax*) is set as 24 hours in our experiment. The number of evacuation vehicles (*VHmax*) is made up of 64 ambulances and 16 helicopters.

Table 6. Summary of principal parameters in the experiment

	p or r	1	2	3		*p*	1	2	3
η_{ip}	*i = 1*	500	1,000	3,500	ρ_{jp}	*j = 1*	150	230	750
	i = 2	500	1,000	3,500		*j = 2*	175	255	950
ϖ_{lp}	ambu	1	2	6		*j = 3*	125	225	550
	heli	2	4	12		*j = 4*	150	245	750
h_r		30	40	50		*j = 5*	120	255	850
φ_r^+		40	50	60		*j = 6*	200	395	1,350
φ_r^-		60	80	100		*j = 7*	225	415	1,550
ϑ_{kr}	*k = 1*	5,000	5,500	5,500		*j = 8*	250	455	1,650
	k = 2	6,000	6,000	7,000	ξ_p		500	250	150
type		θ_l	ζ_l	ν_l		*r*	1	2	3
ambulance		0.10	0.25	50	σ_r		0.14	0.16	0.18
helicopter		0.15	0.45	100	*ETmax*	1,440	*VHmax*	80	

Some principal parameters in the experiment are presented in Table 6. There are 100,000 evacuees in two staging areas at the beginning of the evacuation process, but it is assumed that there are no additional evacuees rescued from disaster fields, and no fatalities occur in staging areas and while transporting to shelters. Each evacuation vehicle has a different speed, capacity, and transportation cost and distance. In particular, if some evacuees are transported from a staging area to a shelter by an ambulance, the ambulance has to move further than a helicopter because ambulances are driven through a road network. The GIS module generates several spatial parameters of the target evacuation routes network and provides the input to the proposed modified BD algorithm. In addition, the total capacity of existing extensive shelters often cannot satisfy the number of evacuees, so the additional candidate shelters have to be selected for evacuees. It is assumed that the capacity of a route (ψ_{ijl}^{t}) does not change with time, so it is fixed regardless of time-based traffic variations. In other words, ψ_{ijl}^{t} is regarded as ψ_{ijl} in this model.

The experiment is first solved using IBM OPL IDE 6.3, ILOG CPLEX 12.1.0 software on a Dell OPTIPLEX 960 with two 3.00 GHz CPU Intel® Core™2 Quad processors and 8 GB RAM. The primary results are shown in Table 3. We also implement the proposed model using ILOG CPLEX 12.1 Callable Library in Microsoft Visual Studio 2012 in order to compare the solutions obtained from the branch-and-cut algorithm and the proposed modified BD algorithm. We use CPLEX MIP and LP solvers to optimize the master problem and subproblems in both algorithms.

Several interesting results are observed when comparing other algorithms such as branch-and-cut and linear programming (LP) relaxation (Table 7). First, the proposed modified BD algorithm has a higher total evacuation cost than all others. When compared to the results of the LP relaxation model, the total evacuation cost of the proposed model increases by 11.74% or $1,961,823. This cost may change with modifications in the initial conditions or some of the other parameters.

Second, the number of 1st priority evacuees transported to shelters in the modified BD algorithm is 1 evacuee lower than in the B&C algorithm, and 11 (or 10.21) evacuees lower than in the LP relaxation algorithm. With the decrease in the number of evacuees evacuated, the total evacuation cost of the proposed model escalates slightly.

Third, the number of iterations and the CPU solution time decreased significantly in the modified BD algorithm. For the modified BD algorithm, CPU solution time is

25.18% lower and the number of iterations is 98.73% lower than experimental results from the B&C algorithm. The variation on the objective evacuation costs along iterations is presented in the Fig. 11.

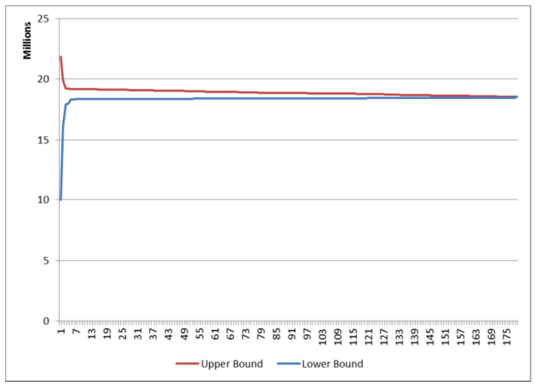

Fig. 11. Convergence of the proposed algorithm

Table 7. Experimental results comparison

	Proposed modified BD	Branch-and-Cut	LP relaxation
Total evacuation cost ($)	18,667,991	18,667,864	16,706,168
Number of formal evacuation shelters	6	6	6.38
Number of 1^{st} priority evacuees	836	837	846.21
Number of solution iterations	179	14,060	12,064
CPU solution time (seconds)	1,526	2,039.54	223.20

IV.6. Summary and conclusion

In this chapter, we have addressed an evacuation modeling to design and solve a LSND problem with an existing road network. A MILP formulation is presented to determine an optimal assignment of evacuees, allocation of evacuation vehicles, location of shelters, and logistics flow of medical resources. In addition, we propose an exact solution approach based on modified BD, which implements faster than the branch-and-cut algorithm. A GIS methodology is applied to the proposed solution approach for the setting of more realistic parameters. Furthermore, in order to examine the applicability and extensibility of the proposed model, we conduct a comprehensive computational experiment using a large-scale realistic instance based on the city of Galveston. Finally, for validating the proposed model, our solutions are compared with other methods derived from traditional solution approaches such as linear programming relaxation and B&C algorithm.

CHAPTER V

CONCLUSION

Developing a timely and effective disaster evacuation model is one of the key strategies of saving lives during LSNDs. The decision-making capability of the model can provide a mechanism for improving disaster response planning. In this thesis, two mathematical modeling methods are addressed to abate the impact of LSNDs. The optimization model 1, TAT model, describes the LSND evacuation procedures with a MILP modeling method and solves the problem by using the B&C algorithm. The model decides on the tactical routing assignment of multiple types of evacuation vehicles in order to transport evacuees with various priorities from affected areas to safe shelters. However, because of several limitations on the modeling and solution approach in the model, the optimization model 2 uses the two-stage optimization modeling method with an existing road network and GIS techniques in order to overcome the restrictions. In addition, we propose an exact solution approach based on modified BD, which implements faster than the B&C algorithm. A GIS methodology is applied to the proposed solution approach for the setting of more realistic parameters. Furthermore, in order to examine the applicability and extensibility of the proposed model, we conduct a comprehensive computational experiment using a large-scale realistic instance based on the city of Galveston. Finally, for validating the proposed model, our solutions are compared with other methods derived from traditional solution approaches such as LP relaxation and B&C algorithm.

In disaster risk management, challenges remain in the trade-offs between the realism of the models that can accommodate the multifaceted complexity of the evacuation process versus their computational intractability. Some future works includes developing a large-scale stochastic optimization model with real-time windows. Another future work would involve conducting agent-based simulation experiments with some statistical methods. In conclusion, we believe that our proposed model can serve as the centerpiece for a disaster evacuation assignment decision support system. This would involve comprehensive collaboration with LSNDs evacuation management experts to develop a system to satisfy their needs.

REFERENCES

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

Andreas, A. K., and Smith, J. C. (2009) Decomposition algorithms for the design of a nonsimultaneous capacitated evacuation tree network. *Networks*, **53**(2), 91-103.

Benders, J. F. (1962) Partitioning procedures for solving mixed-variables programming problems. *Numerische Mathematik*, **4**(1), 238-252.

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

Bish, D. R., Sherali, H. D., and Hobeika, A. G. (2014) Optimal evacuation planning using staging and routing. *Journal of the Operational Research Society*, **65**(1), 124-140.

Bretschneider, S. and Kimms, A. (2011) A basic mathematical model for evacuation problems in urban areas. *Transportation Research Part A: Policy and Practice*, **45**(6), 523-539.

Carr, L. J. (1932) Disaster and the sequence-pattern concept of social change. *American Journal of Sociology*, **38**(2), 207-218.

Centre for Research on the Epidemiology of Disasters (CRED). (2012) EM-DAT: The international disaster data-base. *http://www.emdat.be/advanced-search/*, [Online; accessed January 6, 2014].

Chalmet, L. G., Francis, R. L., and Saunders, P. B. (1982) Network models for building evacuation. *Management Science*, **28**(1), 86-105.

Chen, L. and Miller-Hooks, E. (2008) The building evacuation problem with shared information. *Naval Research Logistics*, **55**(4), 363-376.

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

Cova, T. J. and Church, R. L. (1997) Modelling community evacuation vulnerability using GIS. *International Journal of Geographical Information Science*, **11**(8), 763-784.

Cova, T. J. and Johnson, J. P. (2003) A network flow model for lane-based evacuation routing. *Transportation Research Part A: Policy and Practice*, **37**(7), 579-604.

Crooks, A. T. and Wise, S. (2013) GIS and agent-based models for humanitarian assistance. *Computers, Environment and Urban Systems*, **41**(1), 100-111.

Dantzig, G. B. and Wolfe, P. (1960) Decomposition principle for linear programs. *Operations Research*, **8**(1), 101-111.

De Silva, F. N., Pidd, M., and Eglese, R. (1993) Spatial decision support systems for emergency planning: an operational research/geographical information systems approach to evacuation planning. in *Proceedings of the 1993 International Emergency Management and Engineering Conference*, Sullivan, J. D (ed), Arlington, VA, USA, 130-133.

De Silva, F. N. and Eglese, R. W. (2000) Integrating simulation modelling and GIS: Spatial decision support systems for evacuation planning. *The Journal of the Operational Research Society*, **51**(4), 423-430.

Drabek, T. E. (1986) *Human system responses to disaster: An inventory of sociological findings*, Springer-Verlag, New York, NY.

Dunn, C. E. (1992) Optimal routes in GIS and emergency planning applications. *Area*, **24**(3), 259-267.

Erdelyi, A. and Topaloglu, H. (2010) Approximate dynamic programming for dynamic capacity allocation with multiple priority levels. *IIE Transactions*, **43**(2), 129-142.

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

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

Howitt, A. M. and Leonard, H. B. (2006) Beyond Katrina: Improving disaster response capabilities. *Crisis Response Journal*, **2**(3-4), 52-56.

International Strategy for Disaster Reduction (ISDR) (2004) *Living with risk: A global review of disaster reduction initiatives*, United Nations, Geneva, Switzerland.

International Strategy for Disaster Reduction (ISDR) (2009) *2009 UNISDR terminology on disaster risk reduction*, United Nations, Geneva, Switzerland.

Jarvis, J. J. and Ratliff, H. D. (1982) Some equivalent objectives for dynamic network flow problems. *Management Science*, **28**(1), 106-109.

Johnson, Russ. (2000) *GIS technology for disasters and emergency management*. Environmental Systems Research Institute (ESRI), Redlands, CA, USA.

Kumar, S, Luhandjula, M. K., Munapo, E., and Jones, B. C. (2010) Fifty years of integer programming: A review of the solution approaches. *Management Research and Innovation*, **4**(3), 5-15.

Li, L., Jin, M., and Zhang, L. (2011) Sheltering network planning and management with a case in the Gulf coast region. *International Journal of Production Economics*, **131**(2), 431-440.

Mclay, L. A. and Mayorga, M. E. (2013) A model for optimally dispatching ambulances to emergency calls with classification errors in patient priorities. *IIE Transactions*, **45**(1), 1-24.

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

Miller-Hooks, E. and Sorrel, G. (2008) Maximal dynamic expected flows problem for emergency evacuation planning. *Transportation Research Record: Journal of the Transportation Research Board*, **2089**, 26-34.

Na, H. and Banerjee, A. (2012) A dynamic network disaster evacuation model to transport multi-priority patients. in *Proceedings of the 2012 Industrial and Systems Engineering Research Conference (ISERC)*, Lim, G. and Herrmann, J. W. (eds), Orlando, FL, available in CDROM.

National Oceanic and Atmospheric Administration (NOAA). (2012) *http://www.noaa.gov/,* [Online; accessed December 20, 2012].

Ng, M. and Waller, S. T. (2010) A static network level model for the information propagation in vehicular ad hoc networks. *Transportation Research Part C: Emerging Technologies*, **18**(3), 393-407.

Özdamar, L., Ekinci, E., and Küçükyazici, B. (2004) Emergency logistics planning in natural disasters. Annals of Operations Research, 129, 217-245.

Pidd, M., De Silva, F. N., and Eglese, R. W. (1996) A simulation model for emergency evacuation. *European Journal of Operations Research*, **90**(3), 413-419.

Sayyady, F. and Eksioglu, S. D. (2010) Optimizing the use of public transit system during no-notice evacuation of urban areas. *Computers & Industrial Engineering*, **59**(4), 488-495.

Sheffi, Y., Mahmassani, H., and Powell, W. B. (1982) A transportation network evacuation model. *Transportation Research A: Policy and Practice*, **16**(3), 209-218.

Sherali, H. D., Carter, T. B., and Hobeika, A. G. (1991) A location-allocation model and algorithm for evacuation planning under hurricane/flood conditions. *Transportation Research Part B: Methodological*, **25**(6), 439-452.

Smith, J. C. and Sonuc, S. B. (2011) *An introduction to integer and large-scale linear optimization.* Wireless Network Design: Optimization Models and Solution Procedures, Kennington, J., Olinick, E., and Rajan, D. (eds), Springer Science, New York, NY, 65-97.

Stepanov, A. and Smith, J. M. (2009) Multi-objective evacuation routing in transportation networks. *European Journal of Operational Research*, **198**(2), 435-446.

Tayfur, E. and Taaffe, K. (2009) A model for allocating resources during hospital evacuations. *Computers & Industrial Engineering*, **57**(4), 1313-1323.

Teklu, F. and Sumalee, A., and Watling, D. (2007) A genetic algorithm approach for optimizing traffic control signals considering routing. *Computer-Aided Civil and Infrastructure Engineering*, **22**(1), 31-43.

Tomlin, J. A. (1966) Minimum-cost multicommodity network flows. *Operations Research*, **14**(1), 45-51.

Vitins, B. J. and Axhausen, K. W. (2009) Optimization of large transport networks using the ant colony heuristic. *Computer-Aided Civil and Infrastructure Engineering*, **24**(1), 1-14.

Xie, C., Lin, D. Y., and Waller, S. T. (2010) A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies. *Transportation Research Part E: Logistics and Transportation Review*, **46**(3), 295-316.

Xie, C. and Turnquist, M. A. (2009) Integrated evacuation network optimization and emergency vehicle assignment. *Transportation Research Record: Journal of the Transportation Research Board*, **2091**, 79-90.

Yao, T., Mandala, S. R., and Chung, B. D. (2009) Evacuation transportation planning under uncertainty: A robust optimization approach. *Networks and Spatial Economics*, **9**(2), 171-189.

Yi, W. and Kumar, A. (2007) Ant colony optimization for disaster relief operations. *Transportation Research Part E: Logistics and Transportation Review*, **43**(6), 660-672.

Yi, W. and Özdamar, L. (2007) A dynamic logistics coordination model for evacuation and support in disaster response activities. *European Journal of Operational Research*, **179**, 1177-1193.