Emergency logistics considering traffic congestion

Wang, Qingyi

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

EMERGENCY LOGISTICS CONSIDERING TRAFFIC CONGESTION

QINGYI WANG

School of Mechanical and Aerospace Engineering

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Abstract

Emergency logistics (EL) is the key to alleviate disaster impacts and to accelerate pre- and post-disaster relief operations. Particularly, plannings of emergency supply and evacuation serve a fundamental role to increase effectiveness and efficiency of EL in field practice, and various models have been developed to facilitate the plannings in the past few decades. However, challenges of developing more practical planning models, which incorporate realistic factors and relationships, for real-world applications still exist. Due to the prevalence and huge impacts of traffic congestion phenomena under emergency situations, the thesis focuses on proposing traffic congestion delays incorporated EL planning models with the goal of enhancing EL performances in practice.

Based on an introduction of EL and traffic congestion, the thesis builds on three aspects. First, we conduct a structured literature review on various supply and evacuation planning models to reveal research gaps. Second, a multi-commodity two-stage stochastic programming model that explicitly incorporates traffic congestion delays and a decomposition-based algorithm are proposed to address a two-stage emergency supply planning problem. With a real-world case study, the superiority of the proposed model is verified, and some managerial insights are given. Third, a novel evacuation planning model is developed to address a dynamic evacuation planning problem of debris flow disasters. The model not only integrates three evacuation strategies (mobilization, staging, and routing) to accelerate evacuation but also incorporates human behavior and traffic congestion delays to enhance practicability of resulting plans. The proposed model can assist debris flow early warning systems, and its effectiveness is verified with an illustrative case study, which also aids in generating insights and policy suggestions for improving evacuation performances.

In all, the thesis highlights the importance of considering the traffic congestion factor in formulating more practical and realistic EL planning models. Although incorporating traffic congestion brings about challenges in model formulation and solvability, its benefits of producing insights and enhancing real-world EL operations worth the challenges.

Keywords: Emergency Logistics, Traffic Congestion, Emergency Supply Planning, Evacuation Planning.

Acronyms

ACR: Actual Cumulative Rainfall

BD: Benders Decomposition

BPR: Bureau of Public Road

CL: Critical Line

CRT: Cumulative Rainfall Threshold

CRED: Centre for Research on the Epidemiology of Disasters

CWB: Central Weather Bureau

DMC: Disaster Management Cycle

DFEWS: Debris Flow Early Warning System

DFEWSs: Debris Flow Early Warning Systems

EL: Emergency Logistics

FCR: Forecasted Cumulative Rainfall

FEMA: Federal Emergency Management Agency

FIFO: First-In-First-Out

GBD: Generalized Benders Decomposition

LB: Lower Bound

LMD: Logistics Management Directorate

OR: Operations Research

PAHO: Pan American Health Organization

PCU: Passenger-Car Unit

PCUs: Passenger-Car Units

MIP: Mixed-Integer Programming

MINLP: Mixed-Integer Non-Linear Programming

MEP: Main Exit Point

MEPs: Main Exit Points

MS: Management Science

NGO: Non-Governmental Organization

SWCB: Soil and Water Conservative Bureau

UB: Upper Bound

VDFs: Volume-Delay Functions

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Chapter 1

Introduction

In the past four decades, various natural disasters such as earthquakes, hurricanes, floods, and debris flows, happened more frequently than before, causing increasingly more human sufferings and economical losses. The increasing trends of disaster occurrence and impacts are illustrated in the report of Centre for Research on the Epidemiology of Disasters (CRED) [24] and in the paper of Hoeppe [53].

Specifically, the 2004 Indian ocean tsunami leads to about 280,000 deaths and more than \$4.4 billion loss; the 2008 Wenchuan earthquake in China results in 87,587 deaths and about \$148 billion loss; the 2010 Haiti earthquake causes around 200,000 deaths and nearly \$14 billion loss; the 2011 Japan earthquake and tsunami cost more than \$300 billion; the 2015 Nepal earthquake leads to more than 6000 deaths and about \$10 billion damage. Such statistical numbers highlight the catastrophic impacts of the past major disasters.

Now, each year, more than 500 disasters of all kinds and scales are estimated to strike our planet, killing around 75,000 people and impacting more than 200 million other people [113]. Moreover, it is estimated that the economic losses due to disasters are now reaching an average of US\$ 250 billion to US\$ 300 billion annually [109]. Unfortunately, forecasts suggest that the increasing trend of disaster impacts will continue. It is estimated that over the next 50 years, natural and man-made disasters will increase by five times in number and severity [103]. To reduce disaster-induced human sufferings and economic damages as well as to speed up post-disaster recovery in the future, people

must pay more attention to natural disasters, and more research efforts are indispensable in the disaster relief fields. Notably, as 80% of disaster relief is about logistics [113], the research field of emergency logistics (EL), or humanitarian logistics, is at the heart of disaster relief.

1.1 Emergency Logistics

EL is the most important element in any disaster relief effort, and it is the one that makes the difference between a successful and a failed disaster relief operations [113]. Nearly all disaster management organizations have a function unit to supervise EL. For instance, Federal Emergency Management Agency (FEMA) of US sets up the Logistics Management Directorate (LMD) to be responsible for policy, guidance, standards, execution and governance of logistics support, services and operations, aiming to provide an efficient, transparent and flexible logistics capability for the procurement and delivery of goods and services necessary for an effective and timely response to disasters [37]. To show the big picture of EL, we introduce EL in three aspects, including definition and characteristics, system and operations, and planning.

1.1.1 Definition and Characteristics

Unlike well-defined business logistics, the definition of EL remains ambiguous. Fritz Institute [102] defines EL as “the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary’s requirements.” Sheu [96] defines EL as “a process of planning, managing and controlling the efficient flows of relief, information, and services from the points of origin to the points of destination to meet the urgent needs of the affected people under emergency conditions.” Whatever the definition, EL is essentially a special kind of logistics with unique features. On one hand, just like normal logistics, all EL operations have to be designed or planned in a way that they get the right goods to the right place and distribute goods to the right people at the right time [113]. On the other

hand, EL is characterized by considerable uncertainty and complexity, and it focuses on satisfying urgent demands of victims under a time-critical, chaotic and dynamically changing environment. The thesis adopts the more general EL definition by Sheu [96] in which both relief and evacuation (a service provided in EL) demands of victims are incorporated.

1.1.2 System and Operations

An EL system is a backbone for all EL operations, and it aims to satisfy emergency demands efficiently and effectively by supporting, integrating and coordinating all EL relevant factors, processes and entities at different space and time.

A typical EL system, a two-echelon EL system under centralized control, is shown in Figure 1.1, which illustrates the relationships between four main EL entities.

Figure 1.1: Illustration of a two-echelon EL system

As the brain of an EL system, the command center is responsible for the organization and coordination of various operations. As shown with the dash-dot lines in Figure 1.1, the center receives data, processes data, and returns guidance information to the other three entities. Through such a centralized data processing and guidance feedback mechanism, the collaborations between different entities are enhanced. However, it is possible that the command center does not exist or cannot function after disasters, leading to a decentralized EL system.

The supply sites include various facilities and participants, such as strategical warehouse, shelter, emergency supply producer, and non-governmental organization (NGO). Usually, supplies are pre-processed (*e.g.*, prioritizing, pre-positioning, packaging, material identification and classification) at supply sites. If all supplies are pushed to demands

sites without proper pre-processing, problems, like material convergence and traffic congestion, will occur to reduce EL efficiency significantly.

Through an outer-layer transportation network (the outer layer arrow line in Figure 1.1), supplies are delivered from supply sites to distribution sites. Distribution sites can be established before or after disasters. Just like the distribution centers of normal logistics, distribution sites not only enhance efficiency of last mile distribution but also reduce manpower and transshipment costs through various measures, like sorting, processing, and repackaging of received supplies.

Supplies finally reach demand sites through an inner-layer transportation network (the inner layer arrow line in Figure 1.1). The inner-layer transportation network is mostly located in or near to disaster areas so that it can be severely damaged or overused under emergency situations.

The demand sites are mostly located in disaster areas, and they are the points where various emergency demands, such as supply and evacuation demands, arise. Since achieving the demand data right after a disaster is difficult if not impossible, it is commonly practiced to predict emergency demands in advance according to geographic features, population distributions and structures, and other characteristics of the disaster-prone areas.

The EL system in Figure 1.1 can be modified based on requirements of considered real-world problems and incorporated modeling details. For example, in practical EL operations, a single-echelon EL system, as shown in Figure 1.2, can be applied to transport supplies or evacuees between supply sites and demand sites directly.

Figure 1.2: Illustration of a single-echelon EL system

An EL system not only links EL operations across space but also encompasses dif-

ferent operations at different times, and all these operations have the common aim to aid people in their survival [64]. According to the four-stage disaster management cycle (DMC) [77] in Figure 1.3, the majority of EL operations are conducted in the preparedness and response stages since the two stages are directly related to the disaster occurrence, making urgent demands critical.

Figure 1.3: Disaster management cycle [77]

While preparedness stage operations are conducted to prepare for potential disasters impacts, response stage operations deal with specific emergency situations based on preparation operations and realized disaster impacts. Specifically, operations like forecasting potential demands of supplies (*e.g.*, food, water, temporary shelters, the number of evacuees and medicine) and establishing strategical warehouses and evacuation shelters, purchasing and pre-positioning vital supplies, and planning supply and evacuation routes are practiced in the preparedness stage. For predictable disasters like floods, hurricanes, volcano eruptions and debris flows, most victims are also evacuated in the preparedness stage. In the response stage, main EL operations include estimating actual disaster impacts and urgent demands, activating emergency operations centers and plans, delivering supplies from warehouses to disaster sites, and transporting evacuees from disaster sites to shelters. Caunhye *et al.* [22] provide Figure 1.4 as an illustration of a framework for major EL operations, as well as associated facilities and flows before and after disasters. Particularly, the thesis focuses on the EL operations, facilities, and flows, which are highlighted with bold lines in Figure 1.4.

Figure 1.4: Framework for disaster operations and associated facilities and flows [22]

1.1.3 Planning

Due to the large number of interrelated EL operations, planning of EL operations becomes crucial and indispensable to achieve efficiency and effectiveness in disaster relief. However, EL planning is extremely tough. According to the report of Pan American Health Organization (PAHO) [33], on one hand, EL planning must provide clear answers to the following general logistics planning questions:

- Which tasks must be carried out? How do they relate to all the other activities, and what are the correct sequences for carrying them out?
- Who will be responsible for performing such tasks?
- Who will be in charge of the overall coordination of the logistical system?
- What resources are needed? How, when, and where can they be procured?
- What alternative actions can be implemented once the system is somehow disrupted?

On the other hand, EL planning calls for extra preparatory activities:

- Assessing the vulnerability of key infrastructure,
- Determining the availability of strategic resources for logistical support,
- Reviewing government policies, plans, and preparations.

Besides, EL planning normally faces a large number of uncertain factors, which further complicate the planning process. As a result, various optimization models have been proposed in the past few decades to facilitate the EL planning. In general, such EL planning models can be classified based on the following five aspects:

- Time v.s. Cost

Planning goals vary according to different EL activities, demands, and planning horizons. However, responsiveness (saving time) and cost-efficiency (reducing cost) are two major planning goals. Generally speaking, under emergency situations, more time saved means more lives saved, and more cost saved means more lives helped. As a result, EL planning models can consider one or both of the two goals based on real-world requirements. When the two goals are considered simultaneously, a weighting method is commonly applied to integrate the two goals in one objective function.

- Centralized v.s. Decentralized

A centralized planning process assumes that a central planner (a government in general) exists to aggregate all information to control and plan for other EL players, which may include victims, donors, military, aid agencies, non-governmental organizations (NGOs), and private companies, to achieve systematic optimality. Although a centralized planning process is simple, its central-control assumption is challenged in field practice like in 2010 Haiti earthquake where nearly no central planner exists in the chaotic post-disaster situation. On the contrary, decentralized planning process assumes that each EL player plans for itself without guidance from a central planner. Consequently, decentralized planning models focus more on designing policies and mechanisms to enhance cooperation and coordination between different EL players.

- Static v.s. Dynamic

While a static planning model adopts a single period horizon for long-term strategic EL planning decisions, dynamic planning models focus on time-varying decisions over multiple periods. Although static models are simple and easy to solve, they face challenges to represent time-varying factors. On the contrary, dynamic planning models add flexibility and reality in modeling time-varying EL factors at the price of becoming more complicated to solve even for average-sized instances.

- Single-Stage v.s. Two-Stage

In general, EL planning focuses on operations in two stages, the preparedness

stage and the response stage, of the DMC. The EL operations of the two stages can be planned separately (single-stage) or integrally (two-stage). As the two-stage EL operations are closely related with each other, an integrated two-stage planning aids in achieving more comprehensive and practical plans. However, more single-stage planning models have been proposed in the past due to the difficulties of formulating and solving two-stage planning models.

- Deterministic v.s. Stochastic

Deterministic planning assumes that all planning relevant parameters, like post-disaster demands and capacities, are known in advance. Stochastic planning incorporates uncertain parameters through probabilistic techniques. Specifically, it is common to represent uncertain disaster impacts with scenarios and scenario occurrence probabilities.

In the past few decades, although various EL planning models have been developed to serve as decision support tools, EL planning still faces a lot of challenges. Some common challenges of EL include lack of recognition of the importance of logistics, lack of professional staff, inadequate use of technology, lack of institutional learning, and limited collaboration [103]. Sheu [96] further summarizes main challenges including the ambiguous definition of EL, problems in controlling the timeliness of relief supply and distribution, difficulties in the resource management, and inaccessibility to accurate, real-time relief information. Day *et al.* [30] point out that four most pressing challenges for EL are demand signal visibility and requirements determination, information management and relief activity coordination, disaster relief planning, and managing relationships and developing trust along the supply chain. More recently, Anaya-Arenas *et al.* [3] conclude that designing more complex but realistic planning models and efficient solution methods are two challenges of producing useful EL decision support tools.

To partially deal with such challenges, some important, but commonly ignored, phenomena of EL should be incorporated in an EL planning process. Particularly, traffic congestion phenomena, which delay EL operations, are widely observed in field practice, making such phenomena attractive for more detailed investigations.

1.2 Traffic Congestion

Traffic congestion phenomena are common in daily life, and they are defined as a condition of traffic delay (i.e., when traffic flow is slowed below reasonable speeds) due to the number of vehicles using a road exceeds the design capacity of the transportation network [114]. It has been identified that the direct and indirect costs of traffic congestion to business logistics are huge and traffic congestion has an increasing impact on logistical efficiency [76]. Under emergency situations, more factors (such as significant traffic infrastructure damages, increased transportation demands from supply and evacuation, and emergency traffic control policies) are contributing to serious traffic congestion, bringing about a lot more negative impacts. In emergency situations, traffic congestion can not only increase the anxiety and road rage of victims but also make the organization and control of rescue and relief efforts more difficult, which are commonly mentioned in disaster reports and news. For example,

- Hurricane Andrew (1992): Traffic congestion, which is triggered by debris and heavy traffic, delayed the delivery of mass care by the Red Cross and other voluntary agencies. FEMA Mobile Emergency Response Support detachments also experience delays in moving through the disaster area, taking about 6 hours to travel 30-45 miles in the initial period following the hurricane [82].
- Ya'an Earthquake (2013): On the road to Longmen, a village where most houses were destroyed, so many private cars arrived with relief supplies and police had to turn them away due to heavy road congestion. Later on Sunday, China's cabinet said only official groups would be allowed access to reduce the traffic congestion that was hurting rescue efforts [54].
- Hurricane Irma (2017): The Florida Department of Transportation released traffic counts showing extremely heavy evacuation traffic before Hurricane Irma, such as 4,000 vehicles on I-75 northbound in Lake City, compared to a norm of 1,000. About 1,800 vehicles traveled on I-75 in Collier County, compared to a norm of 600. It is also reported that evacuations before hurricanes commonly face serious traffic congestion problems [36].

Traffic congestion is also discussed in the literature. Fritz and Mathewson [42] point out that the convergence behavior (the informal, spontaneous movement of people, messages, and supplies toward the disaster area) can contribute to heavy traffic congestion on the arterial routes leading to hospitals and medical centers. Thus, it is significant to keep routes clear for the flow of emergency traffic. Feng and Wen [38] indicate that after the Chi-Chi earthquake, traffic congestion, caused by serious transportation infrastructures damages, is a major concern for the on-site operators who are in charge of supplies delivery, evacuation, rescue, and restoration. Extraordinary traffic congestion also happened after the great Hanshin-Awaji earthquake, and it delayed emergency medical services [108]. Recently, Hamada [52] concludes that transportation of equipment/personnel hindered due to traffic congestion is a main reason for long recovery time after an earthquake.

Traffic congestion exists before and after hurricanes. It is mentioned that before Hurricane Katrina, a large number of evacuees caused severe traffic congestion that delayed evacuation [73]. Wolshon [116] notices that after a hurricane, post-evacuation reentries can also generate enormous amounts of transportation demand over a short duration of time, leading to significant congestion, delay, and even traffic safety issues. Bish *et al.* [16] conclude that in fact, most highly populated areas experience congestion as a daily occurrence due to commuter demand, let alone due to the more extensive demands induced by an evacuation that is prompted by a major catastrophe. Moreover, Wen *et al.* [115] carry out a case study for Hurricane Katrina, which reveals that the total indirect cost for the highway system after the hurricane is estimated to be 393.4 million. They also point out that re-routing and congestion delays are the two primary factors accounting for 98.24% of the total daily indirect cost caused by the disruptions and capacity reduction of the highway system after the disaster.

Due to the prevalence and enormous impacts of traffic congestion before and after disasters, it is necessary to consider potential traffic congestion impacts in an EL planning process. Particularly, traffic congestion delay, one major effect of traffic congestion, should be incorporated in strategical EL planning models to produce more realistic and practical plans.

Based on the background introduction of EL planning and the discussions of traffic congestion phenomena, our research scope can be outlined.

1.3 Research Scope

Traffic congestion impacts should be considered in EL planning processes to ensure that resulting EL plans are effective and efficient for field practices. As most EL operations are relevant to emergency supply and evacuation, the research scope is limited to the planning of emergency supply and evacuation with the traffic congestion factor explicitly incorporated. Within the scope, the research is conducted through a literature review and mathematical modeling. A detailed literature review helps to identify research gaps or enhancement areas, and the techniques of mathematical modeling are used to define and fill such gaps effectively.

1.4 Aim and Objectives

The thesis aims to develop novel traffic congestion impacts incorporated EL planning models, which can serve as decision support tools for field practice. Specifically, the proposed models aim to achieve the following objectives:

- 1). Show advantages and benefits of considering traffic congestion impacts in EL planning processes;
- 2). Serve as decision support tools in the field practice of EL planning;
- 3). Aid in understanding the traffic congestion impacts on the optimal EL plans;
- 4). Help to generate managerial insights and policies to effectively mitigate traffic congestion impacts on EL;
- 5). Contribute to upgrading the current EL system or mechanism; and
- 6). Fulfill basic humanitarian goals of EL.

1.5 Organization of the Thesis

The remainder of the thesis is organized into four chapters. Chapter 2 presents a detailed literature review to identify specific research gaps, which are filled by the thesis. Chapter 3 proposes a congestion-delay incorporated two-stage stochastic emergency supply planning model. Chapter 4 develops another model, which aids in integrated evacuation planning for debris flow prone areas. The problem backgrounds, mathematical formulations, case studies, and associated managerial insights of the two proposed models are also discussed in Chapter 3 and Chapter 4, respectively. Chapter 5 summarizes the main contents and contributions of the thesis, as well as discusses our future work briefly.

Chapter 2

Literature Review

EL has absorbed most of the research efforts from the operations research (OR) and management science (MS) communities in recent years. Many researchers contribute in three areas, model, theory, and application [44]. This chapter conducts a comprehensive literature review to identify research gaps, and it consists of six sections. Section 1 presents an overview of previous EL models to show the big picture and research trends. In-depth reviews of emergency supply planning models and evacuation planning models are conducted in Sections 2 and 3, respectively. The approaches of modeling traffic congestion delay with volume-delay functions (VDFs) are reviewed in Section 4. Section 5 summarizes the identified research gaps.

2.1 Overview of Emergency Logistics Research

EL has received contributions from both empirical and quantitative research. While empirical studies in social science and humanitarian areas add insights about EL mechanisms, human behaviors, and some critical factors affecting EL performances, quantitative investigations of various EL models are progressing to provide useful tools and knowledge for optimizing the complicated EL operations in field practice. Now, the fruitful EL models nearly cover every facet of EL operations so that there are a few general literature reviews to summarize various EL models, to reveal study trends, and to guide further investigations as cornerstones.

Caunhye *et al.* [22] provide a structured review on previous EL optimization models under a two-stage (pre- and post-disaster stages) operation framework. They suggest further research directions for EL planning by 1) decomposing main EL activities into pre-disaster operations (including facility location, stock pre-positioning, and evacuation) and post-disaster operations (including relief distribution, casualty transportation, and evacuation) and 2) identifying inherent relationships between two-stage operations. Particularly, they point out that cross-operation models (models that integrate different operations) and multi-objective models are more realistic, but are limited in the previous research.

Diaz *et al.* [32] conduct a review on problems and challenges encountered in EL operations by classifying various models into four groups, transportation/routing, procurement, distribution, and facility location. They draw similar conclusions as Caunhye *et al.* [22] that pre-planning and fast responses are most significant to achieve the effectiveness and efficiency of EL.

The review of Leiras *et al.* [66] shows that most research focuses on the EL operations in preparedness and response stages, highlighting the need for more EL research on recovery-stage operations. Besides, their review suggests closer cooperation between academia and humanitarian organizations with the hope of generating more practical research, which incorporates real-world case studies.

Anaya-Arenas *et al.* [3] carry out a systematic review of relief distribution network models by classifying models into four categories: 1) location-allocation and network design models, 2) transportation (routing) models, 3) integrated location-transportation models, and 4) other topic models. They stress that EL has both theoretical and practical importance. More specifically, they state that advancements in location-allocation models and transportation models are the keys to improve the quality of response to a disaster and to save more lives.

Özdamar and Ertem [84] conduct a survey that focuses on EL models and solution methods for the response- and recovery-stage operations. They highlight the importance of developing integrated EL models and efficient solving approaches for the better decision support of field operations.

Grass and Fischer [49] conduct a detailed literature review on previous two-stage stochastic humanitarian planning models with a particular emphasis on relevant modeling and solution approaches.

Some other literature reviews concentrate on evacuation planning models specifically.

Hamacher and Tjandra [51] present a review for mathematical modeling techniques that can be applied to evacuation problems.

Abdelgawad and Abdulhai [1] discuss the limitations, gaps, and challenges that hinder the development of an integrated optimal evacuation planning model.

More recently, Bayram [9] provides a comprehensive review on modeling and solution approaches of network-based large-scale emergency evacuation planning studies, pointing out the importance of considering realistic factors, like human behavior, shelter location, uncertain and dynamic environments, and interactions between supply and evacuation, in future research.

Based on these general literature reviews, some major research trends of EL can be summarized as follows:

- The trend that EL becomes increasingly important in reducing disaster impacts remains.
- It is better to consider the operations of multiple stages, particularly the preparedness stage and the response stage, with an integrated EL planning process.
- Research on developing more realistic EL planning models and more efficient solution methods deserve further efforts.
- Incorporating realistic factors are vital for developing better EL models in the future.
- Emergency supply planning and evacuation planning are still two dominating and challenging EL topics, which call for more research efforts.

Following the identified EL research trends, an in-depth review of various emergency supply planning models and evacuation planning models is conducted in the next two sections.

2.2 Emergency Supply Planning

Emergency supply planning is the foundation for supply-relevant operations. The primary problems of supply planning include how to effectively prepare various supplies, like water, food, medical kits, and blankets, before disasters, and how to efficiently deliver prepared supplies from strategical warehouses or distribution centers to demand sites after disasters. As the preparedness and response stages of the DMC are directly related to disaster occurrence, most publications about emergency supply planning focus on making decisions in either one or both of the two stages [44,66].

2.2.1 Single-Stage Supply Planning Models

In the preparedness stage, pre-positioning emergency supplies at established warehouses is crucial to ensure that supplies are readily available to satisfy post-disaster victim demands as early as possible. Therefore, the location of supply facilities and the allocation of emergency supplies have been the focus of relevant models.

Batta and Mannur [7] develop covering-location models to deploy supply facilities for emergency situations requiring multiple response units.

Jia *et al.* [57] propose a general facility location model, which can be casted as a covering model, a p -median model, or a p -center model, for large-scale emergencies.

Görmez *et al.* [48] build a supply facility location model based on a p -median model for a two-tier distribution system.

Galindo and Batta [43] build a stochastic supplies pre-positioning model, which allows the possible destruction of supply points during disasters. Besides, their model deals with other key challenges of pre-positioning supplies under a hurricane setting, and it shows that the pre-positioning strategy can lead to significant improvement in the total expected relief cost. Their model can be improved by considering multi-commodity and allowing partial destructions of supply points.

In general, such preparedness-stage facility location models ignore the transportation routes of emergency supplies, which however are significant for the response-stage planning research.

Research in the response stage focuses more on the transportation and allocation of limited supplies, as well as establishing temporary distribution points based on realized disaster impacts. Such operations aim to ensure that emergency supplies can reach victims quickly.

Barbarosoğlu and Arda [6] propose a two-stage scenario-based stochastic programming model to optimize multi-commodity multi-modal supply flows over an urban transportation network for the earthquake response problem. The first stage indicates initial response based on the estimated earthquake scenarios and the second stage represents ongoing response based on the conditional impact scenarios. The model essentially re-allocates the initial supplies between network nodes to satisfy more realized demands, and it reveals the value of information for uncertain disaster impacts.

Lin *et al.* [71] develop a tour-based multi-objective model for emergency supply delivery after a disaster. Their model considers a multi-item, multi-vehicle, multi-period, soft time windows, and split delivery strategy prioritized delivery problem. With a case study, the importance of prioritizing delivery is highlighted. Furthermore, they extend the post-disaster supply delivery research [71] by incorporating decisions of setting up temporary depots with vehicles and resources around a disaster area as well as allocating demand points to temporary depots for logistic efficiency improvement [72].

Murali *et al.* [80] propose a special case of the maximum covering location model to select distribution points and allocate medicines in response to a bio-terror attack. Their model considers distance-sensitive coverage with a loss function and demand uncertainty with chance constraints.

Sheu and Pan [97] develop a modeling method for designing centralized emergency supply networks after disasters. Their method integrates three-stage multi-objective models to design the shelter, medical, and distribution networks in sequence.

Rennemo *et al.* [93] present a stochastic model, which decomposes response-stage operations into three planning stages and considers the opening of local distribution facilities, the initial allocation of supplies, and last-mile distribution of aid, respectively. Their stochastic model produces better solutions than those produced by a deterministic expected value approach.

Khayal *et al.* [59] provide a model for dynamic selection of temporary distribution facilities and allocation of resources in the response stage. Their model shows benefits of considering dynamically changing demand in developing more effective resource distribution plans.

Rivera-Royero *et al.* [94] present a dynamic model to serve demand based on the time-varying urgency of demand nodes. Factors like dynamic demand, capacity constraints, and priorities are incorporated in their model.

Although single-stage models are significant for generating strategic policies and managerial insights, they have the drawback of ignoring the inherent relationship between pre- and post-disaster operations. The drawback not only prevents the collaboration of supply operations over different DMC stages but also compromises the application value of various single-stage models.

2.2.2 Two-Stage Supply Planning Models

We believe that two-stage supply planning models are more practical since they integrate preparedness-stage operations (strategic supply location and allocation) with response-stage operations (temporary distribution point location and supply transportation) in the planning process. To capture uncertain disaster impacts and to represent location-allocation decisions, most of the relevant research papers apply a scenario-based stochastic approach to form various mixed-integer programming (MIP) models.

Balcik and Beamon [5] develop a scenario-based stochastic model that is a synthesis of various extensions proposed for the maximal covering model. Their model integrates facility location and inventory decisions and incorporates factors like multiple commodities, limited budgetary, and restricted facility capacity. With a computational study, they show the effects of pre- and post-disaster relief funding on the performance of the relief system and generate other managerial insights.

Chang *et al.* [25] develop two stochastic programming models for flood emergency logistics planning under different rainfall situations. Their model generates decisions on the structure of rescue organizations and warehouse locations, the required quantities of rescue equipment, and the distribution of rescue equipment simultaneously.

Rawls and Turnquist [90] present a multi-commodity two-stage scenario-based stochastic model to decide facility locations and resource stocking amounts under uncertain disaster impacts, aiming to minimize the expected total cost, which includes the facility establishment and supply stocking costs, and the expected costs of transportation, unsatisfied demand, and undelivered inventory. To solve large-scale instances, they propose a heuristic solution method, a Lagrangian L-shaped method, for their MIP model. A case study on hurricane threats in the southeastern US illustrates that their model and solution method is effective. Rawls and Turnquist [91] further extend the model by incorporating additional service quality constraints on the satisfied demand rate and the shipping distance limit to ensure timely response to demands. Moreover, Rawls and Turnquist [92] propose a dynamic allocation model to optimize pre-event planning for meeting short-term demand at shelter sites under uncertainty. They use a reliability parameter to ensure service quality and analyze the influences of critical parameters.

Döyen *et al.* [35] develop a two-echelon stochastic MIP model that not only opens pre-disaster warehouses and pre-positions supplies but also decides post-disaster rescue centers and transportation.

Lodree *et al.* [75] present a two-stage stochastic supply planning model from the perspective of a single manufacturing facility. It is shown that a proactive inventory pre-positioning strategy is better than a wait-and-see policy for the manufacturer.

Davis *et al.* [29] incorporate warehouse coordination in formulating their two-stage stochastic programming model to determine how supplies should be positioned and distributed among a network of cooperative warehouses. With an extensive computational study, they not only achieve a good operational policy but also discuss tradeoffs between coordination, pre-positioning, and response.

Tofighi *et al.* [104] address a two-echelon EL network design problem that involves pre-positioning supplies at central warehouses and local distribution centers in the first stage, and delivering supplies under multiple objectives in the second stage. Their mixed possibility-stochastic model contributes by incorporating fuzzy parameters into the two-stage stochastic programming framework. For simplicity, the second-stage transportation capacities and routes are ignored.

Alem *et al.* [2] consider the dynamic multi-period nature of disaster relief operations, limited budgets, fleet sizing, and a variety of uncertain data in their stochastic model. They also investigate the benefits of model extensions via various risk measures, such as minimax-regret approach, semi-deviation, and conditional value-at-risk.

Caunhye *et al.* [23] propose a two-stage location-routing model to integrate pre-positioning decisions with after-disaster distributing decisions. Their model illustrates the advantages of integrating two-stage decisions and shows the value of transshipping supplies between warehouses after disasters.

Pradhananga *et al.* [88] present an integrated two-stage stochastic planning model based on a three-tier network structure with multiple supply points. Their model considers a non-linear deprivation cost function for unsatisfied demand and shows that the deprivation cost structure can greatly affect the pre- and post-disaster supply plans. Furthermore, their model indicates that 1) multiple supply sources can ensure the efficient distribution of supplies and 2) partial pre-positioning and post-disaster purchasing can reduce the shortage of emergency supplies.

It is recognized that various EL factors, like warehouse capacity, preparation budget, supply equity, and stochastic disaster impact, have been considered in previous emergency supply planning models. However, few models consider potential road damage and poor road conditions (e.g., poor coverage, high vulnerability, and restricted link capacity) [44]. Meanwhile, post-disaster traffic congestion phenomena are commonly ignored in previous supply planning models. In Davis *et al.* [29], network congestion is considered as an assumed scenario-specific factor to approximate flow travel speed. However, such a simplified congestion factor method fails to represent arc flow capacity relationships leading to traffic congestion.

2.3 Emergency Evacuation Planning

Unlike emergency supply planning, which facilitates the logistics of relief supplies, emergency evacuation planning assists the transportation of evacuees. In the past few decades, various evacuation planning models have been proposed as large-scale evacu-

ation decision support tools to aid in achieving precautionary and life-saving goals of evacuation before and after disasters. For simplicity, such models normally consider evacuation traffic as flows rather than more detailed entities, like individual vehicles. Moreover, the previous models propose four major planning strategies (reversing lanes in the direction of evacuation (contra-flow), staging evacuation processes, optimally controlling traffic, and providing route guidance to evacuees) to improve evacuation efficiency [1].

The diverse evacuation planning models can be categorized as static models and time-varying (dynamic) ones depending on whether the temporal characteristics of evacuation flows are considered or not.

2.3.1 Static Evacuation Planning Models

Static evacuation planning models assume that evacuation flows and conditions are fixed in each period. Such models are simple and easy to solve optimally for relatively large instances. However, their practicability suffers from ignoring the inherent time-varying feature of factors like human behavior, transportation condition, and evacuation demand, which in reality change over time.

Some of the static evacuation planning models focus on shelter location and evacuee flow assignment decisions.

Sherali *et al.* [95] propose a deterministic location-allocation model to establish shelters and to guide evacuation flows under hurricane/flood conditions. By explicitly considering traffic congestion delays, they formulate a mixed-integer nonlinear programming (MINLP) model, and they develop a heuristic and two versions of an exact algorithm based on the generalized Benders decomposition method to solve their model. However, their model ignores the uncertainty of disaster impacts.

Kongsomsaksakul *et al.* [62] relax the centralized control assumption (the authority controls all evacuation decisions) in Sherali *et al.* [95] and build a bi-level model for flood evacuation planning where the authority decides shelter locations and the evacuees choose the shelter and route to evacuate.

Ng *et al.* [81] propose a bi-level evacuation model as well. In the upper level, evac-

uees are assigned to shelters to benefit the entire system, but in the lower level, evacuees show selfish behavior and are free to choose routes to reach their assigned shelters.

Bayram *et al.* [10] develop an evacuation model that not only optimally locates shelter sites but also assigns evacuees to nearest shelters and through shortest paths with a tolerance degree. Their model identifies the importance of convincing evacuees with a relatively higher tolerance level for evacuation routing in producing an efficient evacuation plan. Later, Bayram *et al.* [11] extend the deterministic model to form an uncertain demand and network incorporated two-stage stochastic model. With a potential earthquake case study, the superiority of the stochastic model is emphasized.

Some other static evacuation planning models concentrate on optimizing evacuation flows at intersection crossings of an evacuation network.

Cova and Johnson [27] present a network flow model for identifying optimal lane-based evacuation routing plans. Their model can reduce evacuation delays at intersections by channeling flows and removing crossing conflicts.

Xie and Turnquist [117] propose a model that enables the transportation capacity of an evacuation network to be increased through two network design strategies: lane reversal on roadway sections and crossing elimination at intersections.

Liu and Luo [74] develop a bi-level network design model to locate the optimal set of intersections in an evacuation network for implementing uninterrupted evacuation flow and traffic signal control strategies, which aim to enhance evacuation efficiency and budget utilization.

Considering many evacuation planning parameters are time-varying in reality, we believe that dynamic evacuation planning models are more practical for field applications.

2.3.2 Dynamic Evacuation Planning Models

Dynamic evacuation planning models incorporate time-varying factors, such as evacuation demand loading patterns, road capacities, and traffic conditions, into a planning process, which contribute to enhancing practicability of resulting evacuation plans. However, such models have the drawback of becoming too large to produce optimal solutions

even for small-size instances.

Li *et al.* [68] propose a scenario-based bi-level programming model to optimize the selection of shelter locations. The upper-level problem is a two-stage stochastic location-allocation problem that identifies shelters to be maintained and opened pre- and post-disasters. The lower-level problem deals with evacuees' route reaction to shelter locations, which provides dynamic evacuation flows and travel times on the road network.

Yi *et al.* [119] present a bi-level stochastic programming model to optimize the issuance of evacuation orders. Their model incorporates the highly uncertain evolution of the storm with a scenario tree and the complexity of the evacuees' behavioral reaction to evolving storm conditions. Their model can be further improved by considering multiple types of orders and adopting more realistic assumptions.

A group of dynamic evacuation planning models is based on dynamic network flow models which consider a discrete or continuous time horizon. In dynamic network flow models, it takes time for the flow to pass an arc, the flow can be delayed at nodes, and the network parameters, *e.g.*, the arc capacities, can change in time [63].

Aronson [4] presents a survey of the results, applications, algorithms and implementations for dynamic network flows. Kotnyek [63] introduces the main flow problems in a dynamic network and gives a solution-oriented review of relevant literature.

Particularly, a collection of discrete time dynamic network flow models used in emergency evacuation planning include four types, namely the maximum dynamic flow model, the earliest arrival flow model, the quickest flow or the transshipment model, and the dynamic minimum cost flow model. Hamacher and Tjandra [51] and Dhamala [31] provide a detailed introduction of the four types of models.

Discrete time dynamic network flow based evacuation planning models can be formulated with a time-space (time-expanded) network, which is first introduced by Ford and Fulkerson [41] in solving their maximum dynamic flow problem. The construction of a time-space network is illustrated with Figure 2.1 and Figure 2.2, which show a simple spatial evacuation network and the associated time-space network, respectively.

The evacuation network in Figure 2.1 includes three spatial nodes and arcs, and each

Figure 2.1: Illustration of a simple spatial evacuation network

Figure 2.2: Illustration of a time-space network

arc is associated with a fixed arc transit time, one period. As evacuees can be held at demand node 1 and shelter node 3 over time, the two nodes have a holding arc pointing to themselves. Correspondingly, as shown in Figure 2.2, the time-space network of Figure 2.1 is constructed by duplicating the node-arc structure of Figure 2.1 over multiple time points. Specifically, the time-space network is formed through 1) duplicating the three spatial nodes at each time point (for simplicity, we assume that the evacuation planning horizon is 4 periods so that the time axis has 5 time points), 2) adding the solid arrow lines to enable flows to move between different spatial nodes with the fixed 1 period arc transit time, and 3) adding the dash-dot arrow lines, which enable flows to be held at the demand node and shelter node over time.

With the help of the time-space network technique, a dynamic network flow problem is converted into a static one, and the model formulation becomes straightforward. However, the resulting model is extremely hard to solve since the time-space network and the associated problem size, which depend on the number of time periods on the time axis, can be overwhelmingly large. Thus, a lot of research is dedicated to developing efficient algorithms (exact or heuristic algorithms) for such evacuation planning models. Some contributions are from Hoppe and Tardos [55], Baumann and Skutella [8], Fleischer and Skutella [39], Lim *et al.* [70], and Pillac *et al.* [86].

On the contrary, research that proposes more realistic time-space network based evacuation planning models is few, which may be due to the limited understanding of evacuation systems and mechanisms in field practice.

Bretschneider and Kimms [19] propose a model that aims to minimize the evacuation duration through reorganizing evacuation routing and preventing conflicts within intersections. Their model is a time-space network based dynamic network flow problem with additional variables for the number and direction of used lanes and with additional complicating constraints. They also propose a relaxation and adjustment heuristic approach to solve their model.

Goerigk *et al.* [47] develop a time-space network based model for urban evacuation. Their model not only considers shelter locations, bus and individualize traffic routing, and route risks but also aims to minimize multiple targets, including the total evacuation

time, the risk exposure of the evacuees, and the number of used shelters. A genetic algorithm based approach is proposed to solve their problem heuristically.

Bish and Sherali [15] consider two aggregated-level demand-based strategies, namely staging and routing, in their planning model for large-scale, automobile-based, evacuations with notice. Cell transmission model is used to model traffic flow and incorporate traffic congestion factor. They conclude that aggregate-level plans are easier to implement and more robust than the disaggregate-level (household-level) plans. Furthermore, Bish *et al.* [16] develop another evacuation planning model that applies the household-level staging and routing strategies to minimize the planned evacuation clearance time. The model incorporates evacuation dynamics, congestion, and different evacuee types. By examining the structure of optimal plans, insights of applying the staging and routing strategies in evacuation management are generated. We believe that the research of Bish *et al.* [15, 16] can be further extended with incorporating evacuation mobilization process.

Pillac *et al.* [85] propose, for the first time, an evacuation optimization model that jointly optimizes the decisions of mobilization process (evacuation order time and mobilization resource allocation) and evacuation route planning by incorporating the behavior response of evacuees to the evacuation order. Their model is solved under the goals of maximizing the number of evacuees reaching safety and minimizing the total duration of the evacuation. However, traffic congestion impacts and staging strategies are ignored in their model.

The previous dynamic evacuation planning models commonly assume constant arc traverse time for any flow amount and adopt arc capacity constraints to ensure that arc flow amounts cannot exceed arc capacities. However, traffic congestion impacts, in reality, tell us that a more realistic model should incorporate flow-dependent arc traverse time in the dynamic evacuation planning process. To achieve the goal, some modeling methods have been proposed.

Merchant and Nemhauser [78] assign each arc a flow-dependent cost function and a flow-dependent exit function to account for a flow-time relationship. However, this method leads to a nonlinear and non-convex problem, whose solvability and analysis

face tremendous challenges.

Kaufman *et al.* [58] use a binary decision variable to model the relationship between flow rates and arc transit times based on a generalized time-space network, which is shown in Figure 2.3. Comparing with the time-space network in Figure 2.2, the only difference is that the generalized time-space network adds more arcs at each time point to represent different arc traverse times. The approach of Kaufman *et al.* is simple, but naturally leads to more complicated MIP problems.

Figure 2.3: Illustration of a generalized time-space network

Carey and Subrahmanian [21] model the flow-dependent transit time based on a generalized time-space network and the piecewise linear approximation of arc travel times. However, the model applying the approach cannot be solved with standard network flow algorithms but with generalized LP solvers.

Köhler *et al.* [61] propose a “fan graph”, which introduces additional “regulating arcs” to enforce inflow-dependent transit times without using generalized capacity constraints in Carey and Subrahmanian [21]. The method is still a rough approximation of the flow-dependent transit time behavior, and the solution space of the original problem is relaxed if applying the fan graph method.

Such research enables the feature of flow-dependent arc transit time to be incorporated in discrete-time dynamic network flow based evacuation planning models. To specify the flow-time relationship of traffic congestion delays, VDFs are commonly applied.

2.4 Volume Delay Functions for Traffic Congestion Delay Modeling

In general, the transportation time through a road has a positive non-decreasing nonlinear relationship with the average flow rate of that road, since more vehicles traveling on the road lead to more serious traffic congestion, which decreases the average travel speed and increases the travel time. Such relationship can be modeled with well-defined VDFs, also referred as link performance functions or link capacity functions, in the transportation research field. Branston [18] and Boyce *et al.* [17] present detailed investigations on various VDFs. Particularly, the Bureau of Public Roads (BPR) function and Davidson's function are two most widely used VDFs in network modeling and in field practice to estimate flow-dependent traffic congestion delays.

The BPR function is developed by the US Bureau of Public Roads in 1964 to describe the exponential relationship between arc traveling time and arc flow rate on a freeway network [110]. It is shown as follows:

$$\text{(BPR function)} \quad t(x) = t_0 \left[1 + \alpha \left(\frac{x}{c} \right)^\beta \right],$$

where $t(x)$ is the traffic congestion incorporated arc traverse time when the arc flow rate equals to x , t_0 is the free flow arc traverse time, c is the practical arc capacity, and $\alpha \geq 0$ and $\beta \geq 0$ are tuning coefficients, which are relevant to different road conditions.

As illustrated in Figure 2.4, the BPR function is a convex nonlinear non-decreasing differentiable function and traffic congestion delays become more sudden with the value of the parameter β increases. The BPR function is most widely used to estimate traffic congestion delays on freeway networks mainly for its simplicity. However, as discussed by Spiess [100], the BPR function has some inherent drawbacks, especially when used with high values of α .

In the original BPR function, α equals to 0.15 and β equals to 4, which are commonly used in previous applications. To enhance application of the BPR function, some updated BPR coefficients for freeways and multilane highways are provided in High-

Figure 2.4: Illustration of the BPR function with $\alpha = 0.15$

way Capacity Manual 2000 [106] as illustrated in Table 2.1. It indicates that using the original $\alpha = 0.15$ and $\beta = 4$ tends to underestimate traffic congestion impacts.

Table 2.1: Updated BPR coefficients for freeway and multilane highways

Facility type	Free-flow speed (mile/hour)	α	β
Freeway	75	0.39	6.3
	65	0.25	9
	55	0.1	10
Multilane highway	60	0.9	6
	55	0.8	6
	50	0.7	6

The approach of estimating traffic congestion delays with the BPR function has been applied in evacuation planning models of Sherali *et al.* [95], Kongsomsaksakul *et al.* [62], Ng *et al.* [81], Li *et al.* [68], Bayram *et al.* [10], and Bayram and Yaman [11].

Davidson's function, developed by Davidson [28] in 1966, is another approach for modeling traffic congestion delays. The function describes the flow travel time relationship based on the concepts of queueing theory and it is written as:

$$(\text{Davidson's function}) \quad t(x) = t_0 \left(1 + J \frac{x}{c_u - x} \right),$$

where $t(x)$, x , and t_0 are the same as those in the BPR function, parameter c_u is the ultimate arc capacity, and $J \geq 0$ is the arc-specific tuning coefficient. The shape of the

Figure 2.5: Illustration of the Davidson's function

Davidson's function is shown in Figure 2.5. Unlike the BPR function, which allows that the arc flow rate x exceeds the practical arc capacity c , the Davidson's function strictly requires that $x < c_u$ and it is asymptotic to $x/c_u = 1$. With the increasing of the tuning coefficient J , traffic congestion delay becomes more serious for the same arc flow rate. Due to the ultimate capacity parameter, the Davidson's function is generally more realistic for the modeling of intersection delays and it is seldom applied in the strategic EL planning models.

When applying the BPR function or the Davidson's function, it worths noting that the function $t(x)$ and variable x are the average (steady-state) values of the planned period and the function $t(x)$ is independent of adjacent arc flows. In addition, previous research provides suggestions for proper application of the BPR function and the Davidson's function. The research of Skabardonis and Dowling [98] indicates that the delay estimation accuracy of VDFs can be greatly improved when their tuning coefficient values are based on local conditions instead of general look-up tables with default values. Recently, Mtoi and Moses [79] calibrate and evaluate coefficients of some VDFs for planning applications. They point out that each function is suitable to a particular facil-

ity type, and they prove that the BPR function is more suitable for uninterrupted flow facilities (*e.g.*, freeways/expressways and managed lanes).

Although VDFs are widely applied to estimate traffic congestion delays, they have drawbacks while being applied to disaster cases. For example, some people argue that it can be hard to estimate the parameters of VDFs for disaster cases, especially considering such parameters may vary with locations and time before and after disasters. Moreover, it is criticized that the parameters of VDFs may not fully characterize the disaster impacts on a transportation system. However, we believe that it is valid to apply VDFs for EL planning. First, the drawbacks of parameter setting of VDFs can be resolved with sensitivity analyses of key parameters and with progressing of disaster relevant techniques like data collection and processing, disaster impact simulation and estimation in the future. Second, VDFs are commonly applied in the previous evacuation planning models for disaster cases, indicating that VDFs can, at least partially, characterize the disaster impacts for realizing the EL planning purpose.

2.5 Research Gaps

Based on the structured literature review, three main research gaps are identified and they are summarized as follows:

- No existing emergency supply planning model explicitly considers traffic congestion impacts with VDFs.

Although the BPR function is widely applied in evacuation planning models, no previous emergency supply planning model explicitly considers traffic congestion impacts with the BPR function. However, our literature review suggests to incorporate traffic congestion delays into emergency supply planning for three reasons: 1) traffic congestion delays post-disaster delivery of relief supplies so that relevant managerial insights should be generated to produce congestion control policies, 2) traffic congestion influences the strategical decisions of warehouse location and supply pre-positioning, and 3) an emergency supply planning model can be more general and practical if the traffic congestion factor is incorporated.

- While various natural disasters, like hurricanes and floods, are widely considered in previous evacuation planning models, no previous model explicitly facilitates evacuation planning for debris flow disasters.

Debris flow disasters constitute a significant threat to people living in mountainous and heavy-rainfall areas, where transportation resource is limited and evacuation delay is expected. Although the affecting area of a potential debris flow disaster can be foretasted like hurricanes and floods, the occurrence time and the life threat of a debris flow disaster is more uncertain and more severe than those of hurricanes and floods, which call for specialized evacuation planning models. However, no model focuses on evacuation planning for potential debris flow disasters. To fill the gap, we should propose a dynamic evacuation planning model that fully incorporates the unique features of debris flow disasters and the special conditions of debris-flow prone areas.

- No previous dynamic evacuation planning model integrates the three evacuation enhancement strategies (mobilization, staging, and routing) based on a real-world evacuation system.

An integrated evacuation planning model, which is based on a real-world evacuation operation system, can serve as a more practical decision support tool for field practice. On one hand, such an integrated model can optimize various decisions jointly and to achieve a global optimal evacuation plan. On the other hand, a real-world evacuation system based model can be easily applied without causing extra management and learning costs. As a result, filling the gap has significant application value.

The thesis attempts to fill the identified three research gaps in the next two chapters. While the first gap is attacked in Chapter 3, the other two gaps are dealt with in Chapter 4.

Chapter 3

A Stochastic Programming Model for Emergency Supply Planning Considering Traffic Congestion

In this chapter, a traffic congestion impacts incorporated two-stage supply planning problem is addressed. Three main contributions are achieved. First, we propose a multi-commodity two-stage scenario-based stochastic mixed-integer nonlinear programming (MINLP) model that explicitly incorporates traffic congestion delays with the application of the BPR function. Second, we apply the generalized Benders decomposition (GBD) algorithm to efficiently solve the model, which beats popular MINLP commercial solvers. Third, some managerial insights about warehouse location, supply pre-positioning, and post-disaster traffic control policies are developed with a real-world case study.

The chapter is organized into five sections. In Section 1, the background of the supplies pre-positioning strategy is introduced. Section 2 defines our two-stage supply planning problem formally. Moreover, Section 2 formulates our proposed model and a comparison model that ignores traffic congestion delays like previous emergency supply planning models. Section 3 proposes a GBD based approach for solving large instances. In Section 4, a real-world case study is carried out to illustrate the benefits of our model, to generate managerial insights, and to verify that the proposed algorithm is effective.

Section 5 presents a summary of the chapter.

3.1 Background Introduction

A supplies pre-positioning strategy, the storage of emergency inventories at or near the location where they will be used, is formally derived from military inventory operations. Now, the strategy is commonly practiced before disasters to accelerate post-disaster supply transportation, and it naturally brings about the location-allocation problems that involve two-stage decisions. In the first stage before disasters, warehouse location and supplies allocation decisions are made considering potential disaster impacts. In the second stage after disasters, supplies transportation decisions are determined based on the first stage supplies pre-positioning decisions and the realized disaster impacts. Due to the uncertainties of disaster impacts and close interactions between pre-disaster location-allocation decisions and post-disaster transportation decisions, it is necessary to establish a planning model that integrates such uncertainties and operation relationships. Moreover, to enhance post-disaster transportation, potential traffic congestion delays should be incorporated in the planning model as well.

3.2 Problem Statement and Model Formulation

In general, the emergency supply planning is made through the transportation network $G(N, A)$ of a disaster-prone area. The full set of nodes, denoted as N , includes the major cities or towns, which are also the potential demand nodes or candidate warehouse nodes. Let set A include all arcs, which represent the main roads of that disaster-prone area. Various types of candidate warehouses are incorporated in set L , and setting up a type $l \in L$ warehouse at node $i \in N$ costs F_{il} . Moreover, a type l warehouse has M_l storage capacity, which is the maximum number of supply trucks that the warehouse can hold. For simplicity, all supply and demand amounts are also measured with truck unit as Galindo and Batta [43] do in their model.

Let set K denote the list of main emergency supplies, such as meals, water, kits, medicine, as well as bundle commodities that contain various commodity elements pro-

portionally. The pre-positioning cost for one truck of commodity $k \in K$ is denoted by q^k , which may include the purchasing cost and the management fee. To represent the costs of extra management or spoilage due to pre-positioning too many trucks of commodity k , we penalize each truck of undelivered commodity k with unit truck holding cost factor h^k . Similarly, we penalize each truck of unmet demand of commodity k with parameter p^k to represent the cost of not fully satisfying emergency demands in time. The setting of parameters, p^k and h^k , are based on the research of Rawls and Turnquist [90], where they set holding cost parameter h^k and penalty cost parameter p^k for each unit of commodity k . In reality, our unit truck holding and penalty cost parameters can be time-varying, location-varying and relevant to the demand characteristics of victims. However, as our model is static and considers the averaged state of post-disaster transportation for the centralized strategic planning purpose, it is justifiable to set p^k and h^k and to assume that p^k and h^k are not only known by the planner but also irrelevant to time and space. Furthermore, each type of commodity is associated with a weight factor δ^k to denote its different transportation cost (including the vehicle operating cost and the en route inventory cost) per unit time.

The uncertainties of disaster impacts are represented with a disaster scenario set S . Each scenario $s \in S$ is a possible realization of future disaster impacts and is associated with an estimated occurrence probability P_s . The scenario details are depicted by the scenario-based parameters, which are denoted with superscript s . As disasters can damage or destroy pre-positioned supplies, we use ρ_i^{ks} ($0 \leq \rho_i^{ks} \leq 1$) to describe the available percentage of pre-positioned type k commodity at node $i \in N$ in scenario s . Intuitively, the closer the pre-positioned supplies to the potential demand nodes, the more convenience for transportation, yet the more damage risk to the supplies. To facilitate the conversion between amount and rate, we assume that the emergency transportation is planned for T time periods, and the constant demand rate (trucks of demand per period) of type k commodity at demand node i in scenario s is estimated to be v_i^{ks} . In this way, the total demand amount of type k commodity from node i in scenario s over the T periods can be computed as $v_i^{ks}T$. The setting of the demand rate parameter v_i^{ks} is based on the research of Sherali *et al.* [95], where they let D_i denote a constant rate of

dissipation of evacuees originating at node i over a time horizon T .

Since traffic congestion delays are explicitly considered in our model, the transportation network conditions of each scenario are estimated in detail. We use t_{ij}^s , B_{ij}^s , and U_{ij}^s to represent the free flow transportation time, the background traffic flow rate, and the practical flow rate capacity of arc $(i, j) \in A$, in scenario s , respectively. In general, if using v_{ij} and η_{ij} to denote the practical arc capacity and the free flow transportation time of arc (i, j) under normal situations, respectively, we can assume that $t_{ij}^s \geq \eta_{ij}$, $U_{ij}^s \leq v_{ij}$, and $B_{ij}^s \leq U_{ij}^s$ for the scenarios without traffic congestion, and $t_{ij}^s \geq \eta_{ij}$, $U_{ij}^s \leq v_{ij}$, and $B_{ij}^s \geq U_{ij}^s$ for the scenarios with traffic congestion. Such traffic condition assumption is reasonable considering potential disaster impacts on transportation infrastructures, traffic control policies, and the behavior of victims. For example, when some roads are damaged, the authority may practice a more conservative traffic control policy by setting a lower speed limit or restricting the traffic flows from entering, contributing to longer than normal free flow transportation time t_{ij}^s and less than normal practical capacity U_{ij}^s . The three traffic relevant parameters, v_{ij} , U_{ij}^s , and B_{ij}^s , are measured by homogeneous vehicle flow rates. To convert our truck flows into homogeneous vehicle flows, parameter u , a passenger-car unit (PCU) factor of our truck, is applied. Moreover, we use parameter μ to convert total transportation time into transportation cost. Although real arc flow rates fluctuate in each transient duration, we can simply assume that all transportation flow rates are steady over the T transportation planning periods as Sherali *et al.* [95] do in their research.

Decision variables are straightforward. The first-stage decision variables include y_{il} and r_i^k , which are decided before knowing the outcome of any specific disaster scenario. Binary variables y_{il} decide the location and type of established warehouses. Non-negative variables r_i^k decide the pre-positioned truck amounts of type k supply at each opened warehouse. The second-stage decisions are defined by variables x_{ij}^{ks} , z_i^{ks} , and w_i^{ks} , which are the arc flow rates, the holding inventory rates, and the unmet demand rates of each commodity under each disaster scenario, respectively. It is obvious that $x_{ij}^{ks}T$, $z_i^{ks}T$, and $w_i^{ks}T$ represent the corresponding truck amounts over the T planning periods.

We summarize all notations in Table 3.1. Based on the notations, our pre-positioning

Table 3.1: Notations

Sets

N , set of nodes, which are also the potential demand nodes and the candidate warehouse nodes,

A , set of all transportation arcs,

L , set of warehouse types,

K , set of emergency commodity types,

S , set of potential disaster scenarios,

Parameters

F_{il} , cost of establishing a type $l \in L$ warehouse at node $i \in N$,

M_l , capacity of a type $l \in L$ warehouse,

q^k , pre-positioning cost per truck of type $k \in K$ commodity,

P_s , probability of scenario $s \in S$,

μ , factor converting transportation time to transportation cost,

δ^k , transportation cost weight of commodity $k \in K$,

t_{ij}^s , free flow transportation time through arc $(i, j) \in A$ under scenario $s \in S$,

u , PCU factor of the truck,

α , coefficient of the BPR function, in general $\alpha = 0.15$,

β , coefficient of the BPR function, in general $\beta = 4$,

U_{ij}^s , practical capacity of arc $(i, j) \in A$ under scenario $s \in S$,

B_{ij}^s , background traffic flow rate on arc $(i, j) \in A$ under scenario $s \in S$,

ρ_i^{ks} , available percentage of the pre-positioned type $k \in K$ commodity at node $i \in N$ under scenario $s \in S$,

v_i^{ks} , demand rates of type $k \in K$ commodity at node $i \in N$ under scenario $s \in S$,

T , planning periods for emergency supply transportation,

h^k , holding cost per truck of undelivered commodity $k \in K$,

p^k , penalty cost per truck of unsatisfied demand of commodity $k \in K$,

ζ_{ij}^s , arc capacity estimation factor for arc $(i, j) \in A, s \in S$ (utilized in the comparison model).

Decision variables

$$y_{il} = \begin{cases} 1 & \text{if a type } l \in L \text{ warehouse is established at node } i \in N, \\ 0 & \text{if not,} \end{cases}$$

$r_i^k \geq 0$, truck amount of the prepositioned type $k \in K$ commodity at node $i \in N$,

$x_{ij}^{ks} \geq 0$, truck flow rate of commodity $k \in K$ assigned on arc $(i, j) \in A$ under scenario $s \in S$,

$z_i^{ks} \geq 0$, rate of undelivered commodity $k \in K$ at node $i \in N$ under scenario $s \in S$,

$w_i^{ks} \geq 0$, rate of unsatisfied demand of commodity $k \in K$ at node $i \in N$ under scenario $s \in S$.

strategy based two-stage supply planning problem can be formulated as follows:

$$\begin{aligned}
(\mathbf{P}) \quad \text{Min} \quad & \sum_{i \in N} \sum_{l \in L} F_{il} y_{il} + \sum_{i \in N} \sum_{k \in K} q^k r_i^k \\
& + \sum_{s \in S} P_s \left\{ \mu \sum_{(i,j) \in A} \sum_{k \in K} \delta^k t_{ij}^s \left[1 + \alpha \left(\frac{u \sum_{k \in K} x_{ij}^{ks} + B_{ij}^s}{U_{ij}^s} \right)^\beta \right] x_{ij}^{ks} T + \sum_{i \in N} \sum_{k \in K} h^k z_i^{ks} T + \sum_{i \in N} \sum_{k \in K} p^k w_i^{ks} T \right\}
\end{aligned} \tag{3.1}$$

s.t.

$$\sum_{l \in L} y_{il} \leq 1, \forall i \in N, \tag{3.2}$$

$$\sum_{k \in K} r_i^k \leq \sum_{l \in L} M_l y_{il}, \forall i \in N, \tag{3.3}$$

$$\sum_{j \in N: (j,i) \in A} x_{ji}^{ks} + \frac{\rho_i^{ks} r_i^k}{T} - z_i^{ks} = \sum_{j \in N: (i,j) \in A} x_{ij}^{ks} + v_i^{ks} - w_i^{ks}, \forall i \in N, k \in K, s \in S, \tag{3.4}$$

$$y_{il} \in \{0, 1\}, \forall i \in N, l \in L, \tag{3.5}$$

$$r_i^k \geq 0, \forall i \in N, k \in K, \tag{3.6}$$

$$x_{ij}^{ks} \geq 0, \forall (i, j) \in A, k \in K, s \in S, \tag{3.7}$$

$$z_i^{ks} \geq 0, \forall i \in N, k \in K, s \in S, \tag{3.8}$$

$$w_i^{ks} \geq 0, \forall i \in N, k \in K, s \in S. \tag{3.9}$$

The objective function of Model **(P)** aims to minimize the expected total cost, which is the sum of the first-stage pre-positioning cost and the expected second-stage cost. The pre-positioning cost consists of two terms, the warehouse establishment cost and the supplies pre-positioning cost. The expected second-stage cost is composed of three terms, which in sequence are the expected transportation cost, the expected holding inventory cost, and the expected unmet demand cost. We apply the expected unmet demand cost term in the objective function mainly for two reasons. First, our model is for strategic planning purpose, and it is assumed that the unmet demand cost factor p^k includes various costs associated with each unit of unmet demand for simplicity. Second, the unmet demand term is applied by Rawls and Turnquist [90] so that using

the same objective term can not only simplify the model comparison with Rawls and Turnquist [90] but also highlight the benefits of considering traffic congestions in our model. Moreover, it should be noted that due to the coexistence of the expected holding inventory cost term and the expected unmet demand cost term in the objective function, the decision variables z_i^{ks} and w_i^{ks} have the relationship $z_i^{ks}w_i^{ks} = 0, \forall i \in N, k \in K, s \in S$, indicating that the cases of excess and unmet inventory cannot exist simultaneously at any given node in any scenario.

The BPR function is directly applied in estimating the expected transportation cost. Summing up the emergency supply flow rate and the background traffic flow rate, that is, $u \sum_{k \in K} x_{ij}^{ks} + B_{ij}^s$, provides the total flow rate on arc (i, j) , which is the input of the BPR function to compute the traffic congestion delay incorporated arc traverse time. The term $\sum_{k \in K} x_{ij}^{ks} T$ represents the total supply truck amount passing arc (i, j) over the T planning periods. Thus, multiplying the arc traverse time from the BPR function with the total supply truck amount produces the total transportation time spent on arc (i, j) , which is the input for estimating the total expected transportation cost.

Constraints (3.2) and (3.3) limit the first-stage decisions. Constraints (3.2) ensure that at most one warehouse is established at one node. Constraints (3.2) are general, and they are also applied by Rawls and Turnquist [90]. To establish multiple warehouses at a single node, we can simply duplicate the node and connect the replica to the original node with a zero cost dummy arc. Constraints (3.3) guarantee that supplies are pre-positioned in established warehouses only, and the total pre-positioned truck amount at each warehouse cannot exceed the warehouse capacity. Constraints (3.4) ensure the balance of second-stage supply transportation flow rates at each node. Node $i \in N$ is a warehouse node if $r_i^k > 0$, a demand node if $v_i^{ks} > 0$, a transshipment node if $r_i^k = 0$ and $v_i^{ks} = 0$, and a warehouse-demand node if $r_i^k > 0$ and $v_i^{ks} > 0$. Moreover, Constraints (3.4) implicitly define decision variables z_i^{ks} and w_i^{ks} . The remaining constraints (3.5)-(3.9) set bounds for the binary and the non-negative decision variables.

Our Model (P) is a scenario-based two-stage stochastic MINLP model, and it is also an extension of Rawls and Turnquist's [90] MIP model, which can be formulated with

our parameter setting and notations as the following comparison model **(CP)**:

$$\begin{aligned}
\text{(CP)} \quad \text{Min} \quad & \sum_{i \in N} \sum_{l \in L} F_{il} y_{il} + \sum_{i \in N} \sum_{k \in K} q^k r_i^k \\
& + \sum_{s \in S} P_s \left\{ \mu \sum_{(i,j) \in A} \sum_{k \in K} \delta^k t_{ij}^s x_{ij}^{ks} T + \sum_{i \in N} \sum_{k \in K} h^k z_i^{ks} T + \sum_{i \in N} \sum_{k \in K} p^k w_i^{ks} T \right\}
\end{aligned} \tag{3.10}$$

s.t.

$$u \sum_{k \in K} x_{ij}^{ks} \leq \max \{0, \zeta_{ij}^s U_{ij}^s - B_{ij}^s\}, \forall (i, j) \in A, s \in S, \tag{3.11}$$

Constraints (3.2) – (3.9).

The linear objective function of MIP model **(CP)** is essentially a special case of Model **(P)**'s nonlinear objective function when the BPR function coefficient α equals to 0. Hence, even when traffic congestion exists, Model **(CP)** simply ignores its impacts. Model **(CP)** contains all constraints of Model **(P)**, and additionally it has the arc capacity constraints (3.11), which ensure that the transportation flow rate on each arc cannot exceed the estimated available arc capacity defined by the right-hand-side term $\max \{0, \zeta_{ij}^s U_{ij}^s - B_{ij}^s\}$. The parameter $\zeta_{ij}^s \geq 0$ is a maximum arc capacity estimation factor decided by the planner. Multiplying the practical arc capacity parameter U_{ij}^s and ζ_{ij}^s reflects the planner's estimation on the maximum possible arc capacity for all traffic flows. Since the BPR function allows arc flow rates exceed the practical arc capacity, there is no need to incorporate capacity constraints in our Model **(P)**. Although the proposed Model **(P)** is more complicated than the previous MIP models, Model **(P)** has its merits. On one hand, Model **(P)** contributes to investigating the traffic congestion impacts on the optimal supplies pre-positioning plan and to generating managerial insights. On the other hand, it aids in developing more realistic and effective plans, especially for traffic congestion-prone areas where transportation resources are insufficient and heavy background traffic flows are expected after disasters.

3.3 A Decomposition-Based Solution Approach

It is straightforward to expand all scenario-based constraints to get an equivalent deterministic form of Model **(P)**. For relatively small cases, the deterministic form can be directly solved with commercial MINLP solvers like SBB, DICOPT, and BARON. However, the direct solving strategy is not practical for large-size cases as an enormous amount of constraints are dealt with simultaneously, making the solving process painfully slow if not impossible. Therefore, it is significant to propose solution approaches to accelerate the solving process for large-size instances.

We observe that the constraints of Model **(P)** present an obvious L-shaped structure of scenario-based blocks as illustrated in Figure 3.1. Once the first-stage supplies

Figure 3.1: Illustration of the L-shaped structure of Model **(P)**

pre-positioning decisions are fixed, Model **(P)** can be decomposed into a series of independent nonlinear minimal cost network flow sub-problems. Moreover, we find that the nonlinear terms, introduced by the BPR function, only appear in the objective function and they are convex in the variable definition domain. The decomposable structure and the convex non-linearity insights enable us to apply the famous generalized Benders decomposition (GBD) algorithm to solve Model **(P)**.

The GBD algorithm, developed by Geoffrion [45], is a generalization of the Benders decomposition (BD) algorithm [13] to solve large-size convex MINLP models. GBD employs the convex nonlinear duality theory to iteratively derive optimal cuts and feasibility cuts, which are corresponding to the cuts derived in the BD algorithm. Due to the efficiency in solving small-size sub-problems and the potential to solve independent

sub-problems simultaneously, the GBD algorithm is expected to outperform the direct solving strategy in solving the decomposable large-scale convex MINLP problems with less time. However, the overall performance of the GBD algorithm still depends on the efficiency of solution strategies for the decomposed master problem and sub-problems. Similar to the BD algorithm, if the model is complete recourse, that is, sub-problems are always feasible for any master problem decision values, only optimality cuts are generated. Otherwise, an extra time-consuming process for detecting feasibility and adding feasibility cuts is necessary. Comparing with heuristic algorithms, the GBD algorithm ensures getting an exact (optimal) solution efficiently, which can be desirable for a real-world application.

For our Model **(P)**, once we fix the first-stage supplies pre-positioning decision variables r_i^k to $\hat{r}_i^k$, a total of $|S|$ independent sub-problems are produced. The sub-problem of scenario $s \in S$ can be formulated as problem **(SP-s)**:

$$\begin{aligned}
 \text{(SP-s)} \quad \text{Min} \quad \theta^s = & \mu \sum_{(i,j) \in A} \sum_{k \in K} \delta^k t_{ij}^s \left[1 + \alpha \left(\frac{u \sum_{k \in K} x_{ij}^{ks} + B_{ij}^s}{U_{ij}^s} \right)^\beta \right] x_{ij}^{ks} T \\
 & + \sum_{i \in N} \sum_{k \in K} h^k z_i^{ks} T + \sum_{i \in N} \sum_{k \in K} p^k w_i^{ks} T
 \end{aligned} \tag{3.12}$$

s.t.

$$\sum_{j \in N: (j,i) \in A} x_{ji}^{ks} + \frac{\rho_i^{ks} \hat{r}_i^k}{T} - z_i^{ks} = \sum_{j \in N: (i,j) \in A} x_{ij}^{ks} + v_i^{ks} - w_i^{ks}, \forall i \in N, k \in K, \tag{3.13}$$

$$x_{ij}^{ks} \geq 0, \forall (i,j) \in A, k \in K, \tag{3.14}$$

$$z_i^{ks} \geq 0, \forall i \in N, k \in K, \tag{3.15}$$

$$w_i^{ks} \geq 0, \forall i \in N, k \in K. \tag{3.16}$$

It is evident that all sub-problems **(SP-s)** are always feasible for any $\hat{r}_i^k$ values. Therefore, our Model **(P)** is complete recourse. The objective function (3.12) minimizes θ^s , a free variable representing the total second stage cost of scenario $s \in S$. Each of the $|S|$ sub-problem **(SP-s)** is convex and can be optimally solved by commercial NLP solvers,

like CONOPT and MINOS. The solutions not only provide the optimal transportation plans of each scenario but also give the optimal Lagrangian multipliers λ_i^{ks} of complicating constraints (3.13) for generating the optimality cuts of the master problem. Also, an upper bound (UB) of Model **(P)** is easily obtained after solving all of the $|S|$ sub-problems.

The relaxed master problem of Model **(P)** is deduced according to the nonlinear duality theory. The keys are projecting Model **(P)** onto the (y_{il}, r_i^k) space and approximating Model **(P)** with optimality cuts. For two-stage stochastic linear programs, Van Slyke and Wets [112] develop an L-shaped algorithm, which adds one cut per iteration. Birge and Louveaux [14] propose a method that adds multiple cuts per iteration, and they find that multi-cut can be more efficient because more dual information is passed to the master problem. However, the multi-cut method can suffer from solving the master problem with fast growing size. For a comparison purpose, we apply both methods, the single-cut method and the multi-cut method, to add optimality cuts for the master problem of Model **(P)**, and the resulting two algorithms are referred as single-cut GBD (sGBD) and multi-cut GBD (mGBD), respectively.

For sGBD and mGBD, Model **(P)** is rewritten as Model **(sP)** and Model **(mP)** as follows:

$$(\mathbf{sP}) \quad \text{Min} \quad \sum_{i \in N} \sum_{l \in L} F_{il} y_{il} + \sum_{i \in N} \sum_{k \in K} q^k r_i^k + \bar{f}(y_{il}, r_i^k), \quad (3.17)$$

subject to constraints (3.2)-(3.3), (3.5)-(3.6), and

$$(\mathbf{mP}) \quad \text{Min} \quad \sum_{i \in N} \sum_{l \in L} F_{il} y_{il} + \sum_{i \in N} \sum_{k \in K} q^k r_i^k + \sum_{s \in S} P^s f^s(y_{il}, r_i^k), \quad (3.18)$$

subject to constraints (3.2)-(3.3), (3.5)-(3.6).

It is obvious that only the first-stage decision variables y_{il} and r_i^k appear explicitly in **(sP)** and **(mP)**. Their objective function is the same since $\bar{f}(y_{il}, r_i^k) = \sum_{s \in S} P^s f^s(y_{il}, r_i^k)$ and $f^s(y_{il}, r_i^k) = \theta^s$. The optimal solution of **(sP)** or **(mP)** can be literally found by solving all the second-stage sub-problems (SP-s) resulting from each possible pair of (y_{il}, r_i^k) , which however can be overwhelming. To reduce the number of sub-problems to be solved, the GBD algorithm enables us to begin with a relaxed master problem and

gradually adding linear cuts, which are produced at each feasible (y_{il}, r_i^k) pair, to outer approximate the $\bar{f}(y_{il}, r_i^k)$ term of **(sP)** and the $f^s(y_{il}, r_i^k)$ term of **(mP)** from below.

We use τ to index the iteration of the solving process. In the τ th iteration, the achieved Lagrangian multipliers $\hat{\lambda}_i^{ks\tau}$ of complicating constraints (3.4) and the sub-problem solutions x_{ij}^{ks} , z_j^{ks} , and w_j^{ks} , denoted as $\hat{x}_{ij}^{ks\tau}$, $\hat{z}_j^{ks\tau}$, and $\hat{w}_j^{ks\tau}$, are applied to produce the τ th single optimality cut $Ls^\tau(y_{il}, r_i^k)$ for **(sP)** and the τ th set of $|S|$ optimality cuts $Lm^{s\tau}(y_{il}, r_i^k)$ for **(mP)**, which are defined by (3.19) and (3.20), respectively.

$$Ls^\tau(y_{il}, r_i^k) = \sum_{s \in S} P_s(b^{s\tau} + \sum_{i \in N} \sum_{k \in K} a_i^{ks\tau} r_i^k) \quad (3.19)$$

and

$$Lm^{s\tau}(y_{il}, r_i^k) = b^{s\tau} + \sum_{i \in N} \sum_{k \in K} a_i^{ks\tau} r_i^k, \forall s \in S. \quad (3.20)$$

The slope coefficients $a_i^{ks\tau}$ are:

$$a_i^{ks\tau} = \frac{\hat{\lambda}_i^{ks\tau} \rho_i^{ks}}{T}, \forall i \in N, k \in K, s \in S$$

and the intercept term $b^{s\tau}$ is:

$$\begin{aligned} b^{s\tau} = & \mu \sum_{(i,j) \in A} \sum_{k \in K} \delta^k t_{ij}^s \left[1 + \alpha \left(\frac{u \sum_{k \in K} \hat{x}_{ij}^{ks\tau} + B_{ij}^s}{U_{ij}^s} \right)^\beta \right] \hat{x}_{ij}^{ks\tau} T \\ & + \sum_{i \in N} \sum_{k \in K} h^k \hat{z}_i^{ks\tau} T + \sum_{i \in N} \sum_{k \in K} p^k \hat{w}_i^{ks\tau} T \\ & + \sum_{i \in N} \sum_{k \in K} \hat{\lambda}_i^{ks\tau} \left(\sum_{j \in N: (j,i) \in A} \hat{x}_{ji}^{ks\tau} - \hat{z}_i^{ks\tau} - \sum_{j \in N: (i,j) \in A} \hat{x}_{ij}^{ks\tau} + \hat{w}_i^{ks\tau} - v_i^{ks} \right), \forall s \in S. \end{aligned}$$

According to Equation (3.19), problem **(sP)** can be modified as the single-cut relaxed master problem **(sMP)**:

$$\text{(sMP)} \quad \text{Min} \quad \sum_{i \in N} \sum_{l \in L} F_{il} y_{il} + \sum_{i \in N} \sum_{k \in K} q^k r_i^k + \Theta, \quad (3.21)$$

s.t.

$$\Theta \geq Ls^\tau(y_{il}, r_i^k), \tau \in \{1, 2, \dots, Iter\}, \quad (3.22)$$

Constraints (3.2) – (3.3), (3.5) – (3.6).

Similarly, base on Equation (3.20), problem **(mP)** is rewritten as the multi-cut relaxed master problem **(mMP)**:

$$\textbf{(mMP)} \quad \text{Min} \quad \sum_{i \in N} \sum_{l \in L} F_{il} y_{il}^{\tau} + \sum_{i \in N} \sum_{k \in K} q^k r_i^{k\tau} + \sum_{s \in S} P^s \Theta^s \quad (3.23)$$

s.t.

$$\Theta^s \geq Lm^{s\tau}(y_{il}, r_i^k), \forall s \in S, \tau \in \{1, 2, \dots, Iter\}, \quad (3.24)$$

Constraints (3.2) – (3.3), (3.5) – (3.6).

Due to relaxation, the objective value of **(sMP)** (or **(mMP)**) is a lower bound (LB) of the original problem **(P)**. With the increase of added optimality cuts (3.22) (or (3.24)), the objective value of **(sMP)** (or **(mMP)**), the LB, will gradually converge to the UB of Model **(P)**. The main procedures of sGBD and mGBD algorithms are summarized in Table 3.2.

The master problem size of mGBD increases $|S|$ times faster than that of sGBD since mGBD adds $|S|$ optimality cuts in one iteration while sGBD adds only one optimality cut per iteration. To prevent the master problem size of the multi-cut method from increasing too fast, we can also apply a hybrid approach that combines some scenarios to form fewer cuts each iteration as suggested by Birge and Louveaux [14]. Since we implement sGBD and mGBD algorithms for exact solutions, the master problems are optimally solved by commercial MIP solvers. However, in case that the MIP solvers lose efficiency, we can always apply heuristic solution strategies, like the Lagrangian relaxation method used by Rawls and Turnquist [90], to solve the master problem.

3.4 Case Study

The case study is based on a hurricane threat in the southeastern US, which is presented by Rawls and Turnquist [90] for their MIP model. Three goals are achieved with the case study. First, we show the benefits of our Model **(P)** by comparing the optimal plans

Table 3.2: sGBD and mGBD algorithms

Steps	Procedures
Step 0. Initialization	<p>Initialize iteration counter $\tau = 0$. sGBD: solve (sMP) (mGBD: solve (mMP)) optimally with MIP solver (CPLEX or GUROBI) to obtain the initial values of y_{il}^0 and r_i^{k0} and the objective value obj^0.</p> <p>Set lower bound $LB = obj^0$, upper bound $UB = +\infty$, and convergence tolerance $\varepsilon \geq 0$.</p> <p>Initialize the empty optimality cut set O and the best solution variables.</p>
Step 1. Sub-problems	<p>Parallely solve all sub-problems (SP-s) with an NLP solver to obtain the optimal values of $\theta^{s\tau}$, $x_{ij}^{ks\tau}$, $z_i^{ks\tau}$, and $w_i^{ks\tau}$, and the Lagrangian multipliers $\lambda_i^{ks\tau}$ of complicating constraints (3.4).</p> <p>sGBD: Add the τth optimality cut (3.22) to set O. (mGBD: Add the τth set of scenario based optimality cuts (3.24) to set O).</p> <p>Update UB with $UB = \text{Min}(UB, \sum_{i \in N} \sum_{l \in L} F_{il} y_{il}^\tau + \sum_{i \in N} \sum_{k \in K} q^k r_i^{k\tau} + \sum_{s \in S} P_s \theta^{s\tau})$.</p> <p>If UB is updated, record the best results obtained so far.</p>
Step 2. Convergence test	<p>If $(UB - LB)/UB \leq \varepsilon$, then stop the algorithm with required accuracy.</p> <p>Else continue.</p>
Step 3. Master problem	<p>Update iteration counter: $\tau = \tau + 1$.</p> <p>sGBD: solve (sMP) (mGBD: solve (mMP)) optimally with an MIP solver to obtain the new optimal values of y_{il}^τ and $r_i^{k\tau}$ and the objective function value obj^τ.</p> <p>Update LB with $LB = \max\{LB, obj^\tau\}$.</p> <p>Go to Step 1.</p>

of Model (**P**) and Model (**CP**). Second, we generate managerial insights with sensitivity analyses on some traffic congestion relevant parameters. Third, the effectiveness and efficiency of our GBD based solution strategy are verified.

3.4.1 Parameter Setting

As shown in Figure 3.2 [90], the case has a transportation network that consists of 30 nodes and 56 bidirectional arcs. The 30 nodes represent major southeastern US cities, which are the candidate warehouse locations and the potential demand sites. The 56 bidirectional arcs, denoted with 56 one-way arc pairs, represent four types of major highway connecting the 30 cities in reality, which are illustrated by the four types of lines in the figure.

Figure 3.2: Case study network illustration (from Google Map) [90]

A total of three types of warehouse (Large, Medium, and Small) and three kinds of emergency commodity (Water, Food, and Medical Kits (MK)) are considered in the case. As Model (**P**) denotes warehouse capacities, pre-positioned supply amounts, and emergency demands with truck unit, warehouse and supply parameters (F_{il} , M_l , and q^k)

in Rawls and Turnquist [90] are converted to truck unit reasonably. The supply weight parameters δ^k are assumed additionally. We adopt Rawls and Turnquist's assumption that each type of warehouse costs the same F_{il} at all candidate locations and the parameter values of h^k and p^k are 25% and 1000% of q^k , respectively. The parameters of the warehouses and commodities are listed in Table 3.3 and Table 3.4.

Table 3.3: Parameters of the warehouses

Warehouse type	F_{il} (\$)	M_l (trucks)
Large (L)	18,000,000	7,572
Medium (M)	11,304,000	3,960
Small (S)	1,176,000	360

Table 3.4: Parameters of the emergency commodities

Commodity type	q^k (\$/truck)	h^k (\$/truck)	p^k (\$/truck)	δ^k
Water	5,536	1,384	55,360	5
Food	80,392	20,098	803,920	10
MK	149,172	37,293	1,491,720	1

The case includes a total of 51 scenarios, of which 50 scenarios represent different hurricane impacts and 1 scenario has no hurricane occurrence. The 50 hurricane scenarios can be classified as single storm situations or multiple nearly simultaneous storms situations. We directly apply the Table 4 in Rawls and Turnquist [90] to define the occurrence probability P_s and the detailed hurricane situation of each scenario. Meanwhile, according to the Table 3 of Rawls and Turnquist [90], the key characteristics of 15 sample hurricanes are defined in Table 3.5.

In the table, the unusable arcs represent highways, which are completely destroyed by the hurricane. Hurricanes of categories 3-5 are major hurricanes, which are assumed to destroy 100% of the pre-positioned supplies at landfall nodes. Minor hurricanes belong to categories 1-2 and they are assumed to damage 50% of the pre-positioned supplies at landfall nodes. The pre-positioned supplies at non-landfall nodes are 100% available after the disaster. The demand nodes and their associated supply demand rates (converted from the demand data in Rawls's thesis [89]) of each sample hurricane are listed in the Table A1 of Appendix A. In general, there are multiple demand nodes

Table 3.5: Sample hurricane characteristics

Sample hurricane	Category	Landfall nodes	Unusable arcs
1. Alicia	3	5	(4,5)
2. Camille	5	14	(12,14),(14,15),(15,24)
3. Bonnie	2	22	-
4. Floyd	2	22	(17,20)
5. Andrew	4	11,29	-
6. Opal	3	15	-
7. Isabel	2	21	(21,22)
8. Lili	1	11	(8,12)
9. Katrina	5	13,29	(12,13)
10. Bertha	2	-	-
11. Fran	3	21	(21,22)
12. Dennis	3	-	(15,24)
13. Emily	3	-	-
14. Georges	4	14,30	-
15. Hugo	4	22	-

around a landfall node, and the supply demand rate of a node is negatively correlated with its distance to the landfall node.

Due to modeling differences, other parameters of Model **(P)** are estimated reasonably. As a pre-processing procedure, we classify the arcs of each scenario to assist in generating the scenario-based arc parameters. As the landfall nodes of Hurricanes 10, 12 and 13 are not defined in Table 3.5, we let their largest demand nodes be the landfall nodes. We refer the nodes directly connecting to the landfall nodes as *affected nodes*. Then for each scenario, the 56 arcs can be classified as *unusable arcs* (defined in Table 3.5), *inner-layer arcs* (usable arcs linking the landfall nodes and the affected nodes), *intermediate-layer arcs* (usable arcs connected with the affected nodes, but not with the landfall nodes), and *outer-layer arcs* (usable arcs not belonging to inner layer or intermediate layer arcs). Based on the arc classification of each scenario and Table 3.6, the scenario-based arc parameters, U_{ij}^s , B_{ij}^s , and t_{ij}^s , can be generated. For simplicity, it is assumed that $U_{ij}^s = U_{ji}^s$, $B_{ij}^s = B_{ji}^s$, and $t_{ij}^s = t_{ji}^s$. In Table 3.6, parameters $v_{ij} > 0$ and $\eta_{ij} > 0$ are the normal state arc capacity and the normal state free flow transportation time of each arc $(i, j) \in A$, respectively. For inner-layer arcs and intermediate-layer arcs, we assume that $B_{ij}^s > U_{ij}^s$, which indicates that traffic congestion will appear on those

arcs due to the heavy background traffic flows after hurricanes. The values of v_{ij} are set based on the look-up table of practical capacity for the original BPR curve [34], where freeway capacity is 1,750 vehicles per lane per hour and express way capacity is 1,000 vehicles per lane per hour. Therefore, the parameters v_{ij} of the four types of highways are estimated as 1,000, 2,000, 3,500, and 5,250 vehicles per hour per direction, respectively. Parameters η_{ij} are set according to trip planning data from Google Map. For each arc, we record several arc traveling times during their idle traffic period, and pick the minimum time as η_{ij} . The resulting η_{ij} values of all bidirectional arcs are listed in the Table A2 of Appendix A, which range from 1 hour to 6.2 hours.

Table 3.6: Setting of other scenario-based parameters

Arc types	U_{ij}^s (vehicles/hour)	B_{ij}^s (vehicles/hour)	t_{ij}^s (hours)
Unusable arcs	-	-	-
Inner layer arcs	$0.5v_{ij}$	$0.9v_{ij}$	$1.5\eta_{ij}$
Intermediate layer arcs	$0.7v_{ij}$	$0.8v_{ij}$	$1.2\eta_{ij}$
Outer layer arcs	$1v_{ij}$	$0.5v_{ij}$	$1\eta_{ij}$

It is assumed that our emergency transportation period is 24 hours with the parameter T equal to 24. Moreover, we let the transportation time to cost factor μ be 100 \$/hour and set the PCU factor of truck, u , as 3, which indicates that the impact of a truck on the traffic flow rate is equivalent to three vehicles. As for the arc capacity estimation factor ζ_{ij}^s of Model (CP), we assume that all ζ_{ij}^s are the same. So ζ_{ij}^s can be denoted as ζ , which is 5 in the case. To conduct an illustrative case study, the assumed parameter values make sense, and they are effective. However, for the real-world applications of Model (P), detailed field investigation, data collection, and data processing are indispensable to achieve more reliable parameter values.

3.4.2 Results and Insights

In GAMS, Model (P) is directly solved with the MINLP solver DICOPT, which achieves global optimal solutions for convex MINLP models, and Model (CP) is directly solved with the CPLEX solver. All solving processes run on a desktop computer with the 64-bit Windows 7, 4G memory, and Intel Core i5-3470 @ 3.20GHz CPU. For the base case

input, Model **(P)** has 4,650 constraints and Model **(CP)** has 10,362 constraints, and they both have 26,496 decision variables, among which 90 variables are binary. As the base case is small in size, the MIP model **(CP)** is optimally solved in less than 40 seconds while the MINLP model **(P)** is optimally solved with around 650 seconds. The optimal solutions of Models **(P)** and **(CP)** are compared in Tables 3.7 and 3.8, respectively.

Table 3.7: Plan costs ($\times 10^6$ \$) comparison

Model	Warehouse cost	Inventory cost	Exp. transportation cost	Exp. holding penalty	Exp. demand penalty	Exp. total cost
(P)	36.36	327.73	26	49.54	683.71	1,123.34
(CP)	37.18	337.76	15.79 (35.25)	52.05	667.76	1,110.53 (1,130)

We compare the costs of the two models term by term in Table 3.7. For Model **(CP)**, the numbers in brackets are the *real costs* resulting from adding traffic congestion delays with the BPR function, while the numbers outside brackets are the *nominal costs*, which ignore congestion delays. The nominal expected total cost of Model **(CP)** is about 12.81 million less than that of Model **(P)**. Since Model **(CP)** neglects traffic congestion impacts in its objective function, the 12.81 million objective value gap not only represents the expected cost of traffic congestion but also stands for a budget limit for the planner to spend on reducing traffic congestion impacts. It seems that conducting a congestion control plan that costs more than the budget limit is uneconomical. However, considering other unquantifiable social benefits, we encourage the planner to actively reduce potential traffic congestion delays with a budget that equals to or is slightly higher than the budget limit. On the contrary, the real expected total cost of Model **(CP)**, as shown in the bracket, is about 6.66 million higher than that of Model **(P)**, which proves that when traffic congestion exists, only Model **(P)** achieves the optimal plan for field practice. Although the plan of Model **(P)** has a higher expected demand penalty, the other four cost terms of Model **(P)** are lower. The comparison of cost terms indicates that once traffic congestion impacts are ignored, the resulting plan will suffer from the problems of pre-positioning too many supplies before disasters and organizing inefficient supplies transportation after disasters. Additionally, Table 3.7 shows that the expected total costs

of the two models are mostly caused by the expected demand penalty. The result can be explained by the extreme right-hand tails of the demand distributions and the assigned relatively large penalty parameters, p^k , for unmet demands.

Table 3.8: Supplies pre-positioning plans comparison

Model	Location node	Warehouse type	Water (trucks)	Food (trucks)	MK (trucks)
(P)	10	S	216	144	0
	12	S	130.61	229.39	0
	13	S	360	0	0
	15	S	276	0	84
	19	L	6,432	1,008	132
	20	S	120	240	0
	21	S	288	72	0
	28	M	2,713.39	1,234.61	12
(CP)	12	S	36	324	0
	19	L	6,044.4	1,320	207.6
	25	L	6,267.6	1,284	20.4

The supplies pre-positioning plans of the two models are compared in Table 3.8 to show their differences. In general, the plan of Model (P) reduces the total pre-positioned supplies amount and disperses the storage of supplies at more locations. In both plans, the storage capacity of each established warehouse is fully utilized. Though the total pre-positioned amounts of food (2,928 trucks) and MK (228 trucks) are the same for the two models, Model (P) only stores 10,536 trucks of water in total, which is significantly less than the 12,348 trucks of water prepared by model (CP). Moreover, unlike Model (CP) that deploys two large warehouses and one small warehouse, Model (P) sets up one large warehouse with more medium-size or small-size warehouses to widely disperse supplies pre-positioning. Although both plans establish warehouses at nodes 12 and 19, the pre-positioned amounts of each commodity at these nodes are different. The supplies pre-positioning arrangement of Model (P), summarized as decentralization, contributes to reducing transportation demand and dispersing transportation pressure on more highways after disasters. Thus, the decentralization strategy of supplies pre-positioning is one key to reduce emergency supply delays.

Due to the different first-stage supplies pre-positioning plans, the resulting second-stage transportation plans of the two models are different as well. To illustrate such

differences, we draw the transportation plans of Scenario 43 from Models (**P**) and (**CP**) in Figures 3.3 and 3.4, respectively.

Figure 3.3: Transportation plan of Scenario 43 from Model (P)

Figure 3.4: Transportation plan of Scenario 43 from Model (CP)

As an extreme scenario, Scenario 43 has two nearly simultaneous sample hurricanes (Alicia and Katrina), leading to a total of 16 demand nodes, among which nodes 5, 13, and 29 are the landfall nodes. The transportation plan of Model (**P**) requires dispatching supplies from the deployed 8 warehouses, which leads to a more complicated plan than that of Model (**CP**). Moreover, the two figures show that the transportation plan of Model (**P**) has two distinct features to reduce traffic congestion delays. First, Model (**P**) tries to avoid delivering supplies through arcs where congestion delays are relatively more serious. For example, Model (**P**) utilizes arcs (4,3), (3,2), and (3,1), instead of the more congested inner-layer arcs (5,3) and (5,2) implied by Model (**CP**), to satisfy demands at nodes 1, 2, and 3. Second, Model (**P**) prefers using multiple routes to delivery supplies between two nodes. For example, Model (**P**) plans two routes to deliver supplies from node 28 to demand node 29, while Model (**CP**) simply delivers all supplies through arc (27,29). The identified transportation plan features of Model (**P**), namely, choosing less congested arcs and utilizing multiple routes, contribute to balancing transportation demands with available arc capacities, which is another key to reduce emergency supply delays.

Sensitivity analyses on the main arc-based parameters in the BPR function

As traffic congestion increases the expected total cost of the optimal plan, the decision maker will be interested in knowing what kind of congestion control measure can effectively reduce the expected congestion delays and produce a plan with a less expected total cost. To answer the question, we conduct sensitivity analyses on the three arc-based parameters, B_{ij}^s , U_{ij}^s , and t_{ij}^s of each one-way arc pair. These parameters are the inputs of the BPR function and can directly influence the severity of traffic congestion delays on each arc.

After a disaster, the inner-layer arcs, which directly connect to landfall demand nodes, are expected to encounter the most severe traffic congestion. Therefore, preparing to implement traffic control measures on inner-layer arcs seems most promising to bring about a supplies pre-positioning plan with a less expected total cost. As shown by the all-arc control lines in Figures 3.5 and 3.6, traffic control measures for decreasing the

background traffic flow rate or increasing the practical arc capacity of all inner-layer arcs can reduce the real expected total costs, of both models, but up to a limit. By comparing the slopes of the all-arc control lines in each figure, we also find that an arc capacity control strategy is more effective than a flow rate control strategy. In the two figures, the vertical gaps between the **(P)**-real lines and the **(CP)**-nominal lines represent the limit of traffic congestion control budget, which decreases with the weakening of the estimated traffic congestion. In addition, although the vertical gaps between the two lines (i.e., **(P)**-real: all-arc control and **(CP)**-real: all-arc control) in each figure also narrow with the decrease of the expected traffic congestion, the line of Model **(P)** keeps lower than that of Model **(CP)**. The result not only shows the superiority of our Model **(P)** to achieve the real optimal solution but also indicates that Model **(P)** can be viewed as the generalization of Model **(CP)** for cases where traffic congestion delays exist.

However, preparing to control all inner-layer arcs after a disaster can be expensive for the planner. As an alternative option, a single arc control strategy is proposed and analysed. Of all inner-layer arcs of each landfall demand node, we label the one-way arc pair with the least free flow transportation time as the *key arcs* of that landfall demand node. Instead of managing all inner-layer arcs, the planner can focus on decreasing background traffic flow rate levels or increasing practical capacities of the key arcs. The effects of the single arc control strategy are illustrated in Figures 3.5 and 3.6 through the single-arc control lines. The single-arc control line of Model **(P)** is lower than that of Model **(CP)** as well. Furthermore, it is obvious that an all-arc control strategy always produces a better optimal value than a single-arc control strategy. However, when estimated traffic congestion severity is high due to higher background flow rate levels in Figure 3.5 and lower arc capacity levels in Figure 3.6, the benefit gaps between the all-arc and single-arc control strategies (i.e. gaps between Line **(P)**-real: all-arc control and Line **(P)**-real: single-arc control) are relatively small in the two figures.

Therefore, if the planner has limited resources to reduce expected traffic congestion delays and hopes to minimize influences on background traffic flows, preparing plans that partially recover the capacity of the key arcs can be most attractive and economical. In addition, according to the capacity equation for freeways and unsignalized multi-

Figure 3.5: Sensitivity analysis on the inner-layer arc background flow rate level of Models (**P**) and (**CP**)

Figure 3.6: Sensitivity analysis on the inner-layer arc capacity level of Models (**P**) and (**CP**)

lane roads in Highway Capacity Manual 2010 [106], freeway practical capacity can be estimated through

$$\text{Capacity} = Q \times N \times f_{HV} \times f_p \times PHF,$$

where Q is the ideal PCU capacity, N is the number of available lanes, f_{HV} is the heavy-vehicle adjustment factor which decreases with the increase of heavy-vehicle proportion, f_p is the driver population adjustment factor, and PHF is a peak-hour factor. Thus, the post-disaster capacity enhancement of key arcs should focus on keeping more lanes available by timely repairing damaged roads or removing debris and increasing parameter f_{HV} by restricting entrance of non-emergency heavy vehicles. We highly suggest the planner establish a policy for restricting non-emergency heavy vehicles from entering key arcs after disasters. Such policy can not only decrease the background traffic flows but also increase the practical arc capacity, contributing to reducing traffic congestion delays from two aspects.

Decreasing the post-disaster free flow transportation time can be a third traffic flow control strategy. The strategy can be realized through encouraging vehicles to travel with the normal state speed or with a higher-than-normal speed when safety is ensured. For example, the planner can set a policy to increase the post-disaster speed limit from 65 mile/hour to 80 mile/hour so as to reduce the estimated free flow arc transportation time. As shown in Figure 3.7, the expected total cost of either model decreases with the decrease of the free flow arc transportation time of all inner-layer arcs.

In all, the sensitivity analyses of the three arc-based parameters, B_{ij}^s , U_{ij}^s , and t_{ij}^s , reveal that if the planner sets the traffic control policies before the disaster and prepares to control the post-disaster arc capacity, the background traffic flows, and the free flow transportation time of the key arcs, the resulting supplies pre-positioning plan can be improved.

Sensitivity analysis on the available capacity estimation factor of Model (CP)

Although the capacity estimation factor ζ has no impacts on our Model (P), it can greatly influence the planning result of Model (CP). Results for three different ranges of ζ ($1 \leq \zeta < 1.9$, $1.9 \leq \zeta < 2.3$, and $2.3 \leq \zeta \leq 5$) are depicted in Figure 3.8. It is obvious

Figure 3.7: Sensitivity analysis on the inner-layer arc free flow transportation time of Models **(P)** and **(CP)**

that the line of (P)-real, which is unaffected by ζ , is always lower than the line of (CP)-real. The vertical gap between the two lines is relatively small and stable in the range of $\zeta \geq 2.3$. In the range of $1.9 \leq \zeta < 2.3$, the gap reaches its minimum. However, in the range of $\zeta < 1.9$, the gap between the two lines ((P)-real and (CP)-real) grows rapidly when ζ decreases. Moreover, in that range, the two lines of Model (CP) overlap, indicating no transportation in the plan of Model (CP) when the estimated available arc capacity for emergency supply transportation is little. The gap between the two lines ((P)-real and (CP)-real) indicates that it is better for the planner to simply overestimate parameter ζ when applying Model (CP). In this way, the estimation for ζ is effortless and the resulted real expected total cost of Model (CP) is relatively more close to that of Model (P). The suggestion agrees with the assumption that the arc capacity is infinite or zero in the case study of Rawls and Turnquist [90].

Sensitivity analyses on the transportation cost weight and the unmet demand penalty factor of water

The transportation cost weights and the unmet demand penalty factors can influence the supplies pre-positioning plan as well. Since water accounts for most of the total pre-positioning and transportation amounts, we exam the impacts of the two parameters by

Figure 3.8: Sensitivity analysis on ζ of model (CP)

increasing the weight and penalty factor of water to ten times of their base case values, respectively. The resulting new supplies pre-positioning plans of Model **(P)** are shown in Tables 3.9 and 3.10.

Table 3.9: New pre-positioning plan with the increased transportation cost weight of water

Model	Location node	Warehouse type	Water (trucks)	Food (trucks)	MK (trucks)
(P)	8	S	24	336	0
	10	S	48	312	0
	12	S	360	0	0
	13	S	360	0	0
	15	S	276	0	84
	19	M	2,034	1,782	144
	20	S	360	0	0
	21	M	3,948	12	0
	22	S	360	0	0
	23	S	258	102	0
	27	S	132	228	0
	28	S	204	156	0

With the increase of the transportation cost weight of water, traffic congestion delays are essentially associated with more transportation costs. Thus, as shown in Table 3.9, the new plan strengthens traffic congestion control by two methods, which are decen-

tralizing the pre-positioned supplies at more locations and reducing the total amounts of pre-positioned supplies. Specifically, comparing with the base case plan, the new plan deploys no large warehouse and it establishes more small- and medium-size warehouses at more locations. The total pre-positioned amount of water is decreased from the 10,536 trucks in the base case to 8,364 trucks, while the total amounts of food and MK are the same.

Table 3.10: New pre-positioning plan with the increased unmet demand penalty factor of water

Model	Location node	Warehouse type	Water (trucks)	Food (trucks)	MK (trucks)
(P)	12	L	6,509	937	126
	15	L	7,488	0	84
	19	L	6,835	721	16
	20	S	121	0	239
	27	L	6,538	1,032	2

On the contrary, as shown in Table 3.10, the increase of unmet demand penalty factor of water leads to a more centralized supplies pre-positioning plan, which relaxes traffic congestion control. This is due to the fact that the relative importance of reducing traffic congestion delays decreases when satisfying more expected demand becomes more critical. In the new plan, four large warehouses are deployed to store more water (27,491 trucks) and MK (467 trucks), and less food (2,690 trucks). In the case study of Rawls and Turnquist [90], increasing the unmet demand penalty factor of water leads to more water and less food and MK. In our case, the different trend of the MK amount can be explained by the small transportation cost weight of MK and the incorporated traffic congestion impacts.

Sensitivity analyses on the coefficients of the BPR function

The BPR function is the key to represent the non-linear traffic congestion delays in Model (P) and to calculate the real expected total cost of Model (CP). The two tuning coefficients, α and β , play vital roles in the function. In our base case input, we let α be 0.15 and let β be 4 for simplicity, and we assume that such coefficient values apply to all arcs. However, the two coefficient values vary according to different road conditions in

reality. To exam the impacts of these coefficients, the sensitivity analyses of Models **(P)** and **(CP)** are conducted with the base case input, and their results are shown in Figures 3.9 and 3.10, respectively.

Figure 3.9: Sensitivity analysis of Model **(P)** on the BPR function coefficients

In general, the increase of α and β raises the real expected total costs of both models since higher coefficient values tend to magnify traffic congestion delays and to cause more expected transportation costs. Comparing with Model **(CP)**, Model **(P)** is more robust to the two coefficients. When $\alpha = 1$ and $\beta = 7$, the real expected total cost of Model **(P)** is only about half of Model **(CP)**'s cost, which shows the superiority of our Model **(P)** in producing more reliable plans.

Additionally, the influence of the BPR function coefficients on the traffic control budget limit is shown in Figure 3.11. With the increase of BPR coefficients, the budget limit increases as well. In the extreme case of $\alpha = 1$ and $\beta = 7$, the budget limit can reach 110 million, which is about 9 times the base case budget limit (12.81 million).

In all, we strongly suggest the planner carry out necessary field studies and calibrations to obtain the practical BPR coefficients for each arc so that a more reliable supplies pre-positioning plan and traffic control budget can be generated by Model **(P)**.

Figure 3.10: Sensitivity analysis of Model (**CP**) on the BPR function coefficients

Figure 3.11: Sensitivity analysis of BPR function coefficients on the budget limit of traffic control

3.4.3 Comparison of Solution Approaches

We implement the sGBD and mGBD algorithms in GAMS to verify their effectiveness and efficiency. According to the comparison of various MINLP solvers from Lastusilta *et al.* [65], two MINLP solvers, SBB [20] and DICOPT [50], are generally faster than the other solvers to optimize convex MINLP problems. Thus, we compare the performances of SBB and DICOPT with the proposed mGBD and sGBD algorithms. When running the mGBD and sGBD algorithms, we utilize CPLEX to solve the MIP master problem and call CONOPT for solving the decomposed NLP sub-problems. Moreover, the Gird Facility of GAMS is applied to parallelly solve sub-problems. With the base case input, the performances of the four solution methods are shown in Table 3.11.

Table 3.11: Performance comparison of different solution strategies

Solution strategies	DICOPT	SBB	mGBD	sGBD
Time (s)	652	>100,000	470	24,861
Iterations	-	-	56	1,404
Objective value	1.123E+9	1.123E+9	1.123E+9	1.123E+9

All of the four approaches achieve the same objective value, which proves that the sGBD and mGBD algorithms are effective to solve Model (P) optimally. Furthermore, the solving time comparison supports that among the four methods, the mGBD method is most efficient for solving the base case of Model (P). In fact, mGBD is significantly better than SBB as it applies the decomposable structure of Model (P). Moreover, mGBD takes fewer iterations and less time than sGBD to solve the base case. The result agrees with Birge and Louveaux's conclusion on the multi-cut method for BD that the multi-cut approach is most effective when the number of realizations (scenarios) is not significantly larger than the number of first-stage constraints [14]. Our base case brings about 51 realizations and 60 first-stage constraints, which satisfies the condition in Birge and Louveaux's conclusion. As GBD based algorithms can attack large-size problems in small pieces iteratively and parallelly, we believe that sGBD and mGBD algorithms are more efficient and practical than commercial MINLP solvers for solving large-scale instances of Model (P).

3.5 Summary of the Chapter

In this chapter, we propose Model **(P)**, a stochastic two-stage multi-commodity supply planning model, to facilitate practicing the emergency supplies pre-positioning strategy. By explicitly considering traffic congestion delays with the application of the BPR function, Model **(P)** generalizes the previous MIP planning model so that it can achieve optimal emergency supply plans for post-disaster scenarios with expected traffic congestion delays.

A real-world case study on a hurricane threat in the southeastern US is conducted to show the advantages of Model **(P)**. Comparing with Model **(CP)** that ignores traffic congestion impacts like the previous MIP model in the literature, Model **(P)** achieves a better objective value (the real expected total cost) through decentralizing supply storage and reducing total pre-positioned amounts of certain supplies before the disaster, as well as through balancing transportation demand (arc flows) with transportation supplies (practical arc capacities) in terms of choosing less congested arcs and utilizing multiple routes for transportation after the disaster. The optimal value gap between Model **(P)** and Model **(CP)** represent a budget limit for controlling traffic congestion delays. Although it seems uneconomical to spend more than the budget limit on reducing potential after-disaster traffic congestion delays, we believe that the value of reducing traffic congestion delays actively is more than the budget limit when considering other unquantifiable social benefits. Thus, we encourage the planner to set a budget that equals to or slightly exceeds the budget limit to reduce potential traffic congestion delays. With sensitivity analyses, we find that setting policies that ensure enough capacity for the key arcs after the disaster is most effective to reduce expected traffic congestion impacts, which highlights the importance of pre-disaster traffic control planning. Particularly, we recommend the authority to establish and announce the policy of restricting non-emergency heavy vehicles from entering the key arcs once a disaster occurs. In addition, we find that the plan result of Model **(CP)** is sensitivity to its arc capacity estimation factor ζ_{ij}^s , and simply assuming a big ζ_{ij}^s value for all arcs under all scenarios is reasonable when applying Model **(CP)**. Comparing with Model **(CP)**, the real expected total cost of Model **(P)** is less sensitivity to the BPR function coefficients α and β . However, it

is necessary to obtain the specific BPR coefficients for each road when applying Model **(P)** in field practice.

Although Model **(P)** can be directly solved in an extensive form with commercial MINLP solvers (like SBB and DICOPT) for small-size cases, we apply the GBD algorithm to propose the sGBD and mGBD approaches for solving large-size instances. With the base case inputs, we find that the mGBD algorithm has better performance than the popular MINLP solvers (SBB and DICOPT). The efficiency of mGBD and sGBD comes from applying the L-shaped decomposable structure of Model **(P)**, as well as from the parallel solving of the independent sub-problems. We believe that the benefits of the GBD-based approach will be more pronounced as the problem size grows.

In all, the chapter proves that potential traffic congestion delays should not be ignored for emergency supply planning. If we don't value the real cost of congestion delay incorporated supply transportation, we have to pay more for our emergency supply plan in field practice.

Chapter 4

An Integrated Evacuation Planning

Model for Potential Debris Flow

Disasters

In this chapter, a dynamic evacuation planning problem of debris flow disasters is addressed. The chapter mainly contributes in two aspects. First, based on the debris flow early warning system (DFEWS) of Taiwan, a novel dynamic evacuation planning model is proposed. The model not only integrates three evacuation strategies (mobilization, staging, and routing) to accelerate evacuation before potential debris flow disasters but also incorporates human behavior and traffic congestion delays to generate more realistic and practical plans. Second, with an illustrative case study, some insights and policy suggestions are produced for improving the performances of debris flow evacuations.

The remainder of the chapter is organized as follows. Section 1 introduces the significance and background of evacuation planning for potential debris flow disasters. Section 2 formally defines the evacuation planning problem and formulates our proposed model. Section 3 conducts an illustrative case study to verify that the model works. Moreover, sensitivity analyses and modeling comparisons are carried out to generate insights. Section 4 presents a numerical experiment to compare solution qualities of different cases and to discuss challenge of solving our model. Section 5 discusses the application benefits of our proposed model, and Section 6 concludes the chapter.

4.1 Background Introduction

A debris flow is a natural phenomenon that a moving mass of loose mud, sand, soil, rock, water, and air that travels down a slope under the influence of gravity [60]. However, the natural phenomenon becomes a disaster once it results in casualty, loss of life, or property. In general, a debris flow may happen when the three main causes (sufficient water, loose debris sources, and steep slopes) exist in the same time [99]. Thus, a debris flow disaster is a common and major threat to people, who live in mountainous areas with frequent rainstorm or heavy rainfall.

Debris flow disasters are dangerous. On one hand, the occurrence time of a debris flow disaster is hard to estimate, which adds preparation challenges. On the other hand, a debris flow can unexpectedly occur with a huge debris volume and a fast moving speed, making it nearly impossible for victims to response. In fact, debris flow disasters have caused massive losses of life and property. In April 2017, a debris flow due to intense rainfall occurred in the Colombian city, Mocoa, killing at least 329 people, injuring 332, and leaving 70 others missing [87]. In August 2010, a disastrous debris flow occurred in Zhouqu city, China, which caused 1557 deaths, 284 missings, and many casualties [101]. In August 2009, the excessive rainfall from Typhoon Morakot resulted in a severe debris flow disaster at Xiaolin village, Taiwan, which killed more than 400 people and wiped out the entire village [26]. Such catastrophic events stress the importance of preparing for debris flow disasters and reducing disaster impacts, which can be achieved by measures of identifying debris-flow-prone areas, educating and governing people who live in those areas, limiting development in debris flow hazard areas, and developing debris flow mitigation plans [60].

Particularity, emergency evacuation is one of the most effective and commonly applied debris flow mitigation plans, and it is supported by various debris flow early warning systems (DFEWSs).

4.1.1 Debris Flow Early Warning Systems

To facilitate evacuation mobilization and to enable all victims to arrive at safe places before potential debris flow disasters, various DFEWSs have been developed for use in the high-debris-flow-risk areas of USA, Japan, and Taiwan.

The Debris-Flow Warning System, implemented in the US, provides time-space specific statements of Outlooks, Watches, and Warnings to allow for useful leading and planning times for system users [40]. An Outlook statement is given when the estimated precipitation exceeds a 10-year recurrence storm for a given area, A Watch statement is announced when a debris flow is highly probable according to the precipitation data, and A Warning is issued when the rainfall data indicate that debris flows are imminent or have a high probability of occurring. According to a report on the warning system, lead times of 24 to 48 hours for issuing Outlooks and Watches, and 24 hours for giving Warnings are desirable [40].

The early warning system in Japan is based on regional critical lines (CLs). The CLs are formed with the 60-minute cumulative rainfall index and the soil–water index, and they are developed for each debris-flow-prone area specifically. The early-warning information is issued when the CL is estimated to be exceeded according to actual and forecast rainfall data. The warning information in Japan includes 4 levels. Levels 1-3 indicate that the forecast rainfall can exceed the regional CL in 3 hours, 2 hours, and 1 hour, respectively, and Level 4 indicates that the disaster is imminent. Moreover, voluntary evacuation and compulsory evacuation are suggested by the level 2 and level 3 warning information, respectively [83].

We are most interested in the DFEWS in Taiwan for its simplicity. The DFEWS gives a yellow alarm and a red alarm to initiate voluntary and compulsory evacuations, respectively. The mechanism of the early warning system is illustrated in Figure 4.1. As shown, the system is based on the cooperation of the three governmental authorities, the central weather bureau (CWB), the soil and water conservative bureau (SWCB) and the local government. In general, CWB is responsible for providing rainfall information to SWCB, who decides regional cumulative rainfall threshold (CRT) and the time of issuing evacuation alarms. The local government takes charge of organizing evacuations

Figure 4.1: The debris flow early warning system in Taiwan

according to the issued alarms from SWCB. In the warning system, the CRT plays the key role in deciding when to give yellow and red alarms. When the forecasted cumulative rainfall (FCR) for the next 24 hours exceeds CRT, the yellow alarm is given, and voluntary evacuation is suggested. Once actual cumulative rainfall (ACR) exceeds CRT, the red alarm is issued to initiate a compulsory evacuation process. The system assumes that once ACR exceeds CRT, a debris flow disaster will occur with a high probability. To reduce the chance that people are not evacuated to safe places when a debris flow disaster occurs, the CRT value tends to be set conservatively. However, a lower CRT value can lead to more frequent yellow alarms, which may cause the "wolf-crying" effect that the residents finally refuse to trust the alarms after several times of unnecessary evacuations.

The successful implementation of a DFEWS is supported by two techniques, identifying debris-flow-prone areas and estimating the potential disaster occurrence times in advance. The debris-flow-prone areas can be recognized with field investigations, simulations, physical models, and other civil engineering techniques, like applying sensitive seismographs to detect slight land moving. After identifying debris-flow-prone areas, the evacuation relevant data (such as the locations and evacuation demands of threatened households, the main exit points (MEPs) of the local transportation network, the locations and capacities of candidate shelters, and the capacity and structure of the main evacuation network) of those areas can be easily achieved to support evacuation planning and organization decisions. In general, the forecasts of debris flow occurrence time are based on radar precipitation estimation and established rainfall intensity-duration (or other rainfall-based) threshold values. The forecast method is derived from the statistical analysis of historical rainfall and debris flow data, and it essentially assumes that a debris flow may occur once a critical rainfall threshold is surpassed by actual rainfall. Thus, if the forecasted rainfall intensity is strong, a critical rainfall threshold can be exceeded in a short time to trigger a potential debris flow disaster, which also indicates that the estimated time horizon for safe pre-disaster evacuation is relatively short. Unfortunately, it is impossible to achieve an exact estimation of a debris flow occurrence time in advance.

Although current DFEWSs tell evacuees when to start voluntary or compulsory evacuations, they are independent of other evacuation planning decisions, and they provide no information on how to evacuate with a short evacuation clearance time. Thus, we believe that a better practice of debris flow evacuation calls for a DFEWS-based dynamic evacuation planning. The following three reasons support the belief.

First, there are close relationships between a DFEWS and evacuation planning. In fact, the alarm decisions of a DFEWS control the evacuation demand loading pattern over time, which is the input of other evacuation planning decisions. Thus, a DFEWS-based evacuation plan can produce global optimal evacuation plans and is more practical for field applications.

Second, the proposed evacuation planning aids in evaluating the effectiveness of a DFEWS. For example, if the planning indicates that the evacuation can be efficiently finished within a short time, it makes no sense to follow the DFEWS to give the voluntary evacuation order too early. On the contrary, if the planning shows that the evacuation requires a long time to finish, it is also unreasonable to follow the DFEWS to give orders late, which indicates that the government should revise the DFEWS or perform other operations to accelerate the evacuation.

Third, such a DFEWS-based dynamic evacuation plan benefits both evacuees and governments. On one hand, the planning results can not only prevent too late or too early evacuation but also help evacuees reach candidate shelters quickly, safely, and smoothly, which increases social satisfaction with the evacuation. On the other hand, the planning reduces evacuation management challenges faced by governments. Following the planning results, governments are more confident to put forward preparing policies and measures to organize a successful evacuation.

As mentioned, a DFEWS-based dynamic evacuation planning can improve the effectiveness and efficiency of evacuations for potential debris flow disasters. However, a practical and realistic plan calls for consideration of the two factors, alarm response behavior of evacuees (*i.e.* S-curve demand loading pattern) and traffic congestion delays, which are discussed next.

4.1.2 S-Curve Demand Loading Pattern and Traffic Congestion Delays

Consideration of S-curve demand loading pattern and traffic congestion delays contributes to enhancing practicability of resulting evacuation plans. Moreover, it is a reasonable requirement of conducting DFEWS-based evacuation planning.

A DFEWS normally issues voluntary evacuation order first. Thus, the response behaviors of evacuees to the order form an evacuation demand loading pattern that should be incorporated in the evacuation planning. In general, it is difficult to forecast the exact evacuation time of each household after the voluntary evacuation order. However, the response behavior of a community tends to form an S-curve evacuation demand loading pattern, which was first introduced by Lewis [67]. The S-curve loading pattern indicates that the evacuation rate starts low right after the voluntary evacuation order, then it increases sharply as more evacuees begin to move, and finally, the evacuation rate becomes low again. An S-curve can be approximated by various mathematical models, such as the Rayleigh distribution approach, the general S-curve formula, and the Sequential logit model. Yazici and Ozbay [118] provide a detailed review on comparing popular S-curve mathematical models. In the study of Li *et al.* [69], the widely used S-curves with different mathematical functions and the state-of-art behavior models are calibrated and compared with empirical data. They find that the calibrated S-curves with Logit and Rayleigh functions fit empirical data better. The S-curve demand loading pattern is applied in previous evacuation planning research, such as Sherali *et al.* [95] and Li *et al.* [68], to increase the application value of proposed models. It should be noted that as the S-curve demand loading pattern can be influenced by factors like the population size, composition of evacuees, severity of potential disasters, geographic characteristics, evacuation resource availability, *etc.*, more regional investigations and scenario analyses are indispensable for applying a proper S-curve in practice. Intuitively, the S-curve can be steeper (people begin their evacuation earlier) for a disaster prone area where the population is large, the potential disaster severity is high, and the evacuation resource is insufficient. Moreover, due to the compulsory evacuation order of a DFEWS, we can assume that the S-curve demand loading pattern ends at the compulsory evacuation

order time and that all left evacuation demands are loaded immediately right after the compulsory evacuation order.

The necessity of considering traffic congestion delays in the evacuation planning is justified by two main reasons. First, the compulsory evacuation order of a DFEWS can cause serious traffic congestion delays during evacuation. Specifically, if a compulsory evacuation order is issued early, substantial evacuation demands will be put on the evacuation network in a short while to induce traffic congestion delays. Second, the environment of debris flow evacuation requires traffic congestion delays to be explicitly considered. Most debris flow evacuations are practiced in mountainous areas, where transportation capacities are insufficient, and traffic congestion delays are common. To fully utilize the limited transportation capacities for a fast evacuation, traffic congestion delays should be considered. Traffic congestion delays relevant models and modeling approaches are reviewed in Chapter 2, which establishes a solid foundation for us to incorporate the traffic congestion delay factor in our evacuation planning model.

4.2 Problem Statement and Model Formulation

The section formally defines the DFEWS-based dynamic evacuation planning problem first. Then, our time-space network based MIP model is formulated to deal with the planning problem.

4.2.1 A DFEWS-Based Dynamic Evacuation Planning Problem

In general, a DFEWS-based dynamic evacuation planning problem arises when a government hopes to integrate the DFEWS warning decisions and other evacuation relevant decisions in the evacuation planning for debris-flow-prone areas. The planning problem can be defined with any DFEWS, which gives voluntary and compulsory evacuation orders officially. For simplicity, we apply the DFEWS of Taiwan, the one that issues yellow and red alarms to mobilize evacuation, to describe the planning problem.

The DFEWS-based dynamic evacuation planning problem is based on the following key assumptions: 1) except the debris flow occurrence time, all other evacuation relevant

data (such as the evacuation demand and location of each household, shelter capacities, and evacuation network configuration) are known; 2) the government aims to achieve a system optimal evacuation plan so that all evacuees are under the centralized control of the government to conduct evacuation; 3) there is no evacuation before the yellow alarm time (the time that $FCR > CRT$ based on the DFEWS of Taiwan), which is set as the time 0 of the evacuation planning horizon; 4) self-evacuations from households to regional MEPs are ignored considering their relatively short distances, and all evacuees follow guided evacuations from the MEPs to the candidate shelters, whose capacities are limited; 5) a debris flow disaster occurs at an uncertain time after the yellow alarm, and the red alarm must be issued at a properly planned time; 6) it is required to enable all left victims to depart from MEPs within a specific time after the red alarm.

Three strategies (mobilization, staging, and routing) are considered in the planning problem to accelerate evacuations for debris flow disasters. The mobilization strategy is supported by the orders of the implemented DFEWS. Since we assume that the yellow alarm is given at time 0 to initialize voluntary evacuation, only the red alarm time needs planning for initiating compulsory evacuation. The staging strategy is implemented by assigning the demand of each household to a main exit point (MEP) and by temporarily holding evacuees at MEPs. The routing strategy is realized by guiding evacuation flows from MEPs to candidate shelters efficiently.

The three strategies affect evacuation in time and space. The mobilization strategy influences the loading times of evacuation demand. The staging strategy can not only disperse loaded evacuation demand over time but also decide the distribution of total evacuation demand among MEPs. The routing strategy decides the evacuation flows over time and space. In all, the evacuation planning problem integrates four main decisions, that is, the red alarm time, the household assignments to MEPs, the holding arrangements at MEPs, and the routing of evacuation flows from MEPs to shelters. Particularly, the red alarm time decision and the household assignment decision together decide the realized demand loading pattern of evacuees at each MEP.

Two goals are considered in the evacuation planning. The fundamental goal is minimizing the planned evacuation clearance time, the time that all evacuees reach candidate

shelters. As the occurrence time of a debris flow disaster is uncertain, and the disaster may occur when some evacuees are still en route, the planning incorporates a secondary goal to minimize the expected disaster occurrence impacts to en route evacuees.

4.2.2 Model Formulation

As a time-space network can express the relationships and positions of events or actions in time and space and convert a dynamic model formulation into a static one, we apply the technique to develop our DFEWS-based dynamic evacuation planning model.

The time-space network construction of our planning problem is illustrated with the simple spatial evacuation network in Figure 4.2. The network has one node for each type

Figure 4.2: The illustrative spatial evacuation network

of spatial nodes (MEP node, transshipment node, and shelter node) in our evacuation problem. To ensure that the network has a single origin-destination pair, a super source node (o) and a super sink node (e) are added to connect all MEP nodes and all shelter nodes with dummy arcs, respectively. Moreover, as evacuees can be temporally held at MEPs, each MEP node has a holding arc pointing to itself.

To construct the corresponding time-space network, a discrete time set of the evacuation planning horizon is decided first. The evacuation planning horizon after the yellow alarm time (time 0) is decided case by case. However, as the planning horizon is an upper bound of the evacuation time that is needed by the model, it should be long enough to ensure that a feasible evacuation plan exists to enable all evacuees to reach shelters. Discretizing the planning horizon into τ periods leads to the discrete time set $T = \{0, 1, 2, \dots, \tau\}$.

Given the spatial network in Figure 4.2, the discrete time set T , and our evacuation planning problem, a normal time-space network is established in Figure 4.3. The hori-

Figure 4.3: The normal time-space network of the spatial network in Figure 4.2

zontal axis denotes time while the vertical axis represents space. The spatial nodes 1, 2, and 3 are duplicated at each time point to represent their state across time. Each node in the time-space network can be indexed as a pair of spatial node index and time point index. The super source node (o) and the super sink node (e) are not duplicated, and they are positioned at time 0 and τ , respectively.

Based on our evacuation problem, three types of arcs, which are labeled with (1)-(3), are included in the time-space network. The type (1) arcs, shown with the dashed arrow lines in Figure 4.3, are demand loading arcs, which ensure that all evacuation demands are loaded from the super source node to the time-expanded MEP nodes, as well as demand converging arcs, which ensure that all demands finally arrive at the super sink node. Such dummy arcs are associated with infinite capacity and a zero arc traverse time. The type (2) arcs, shown with the dash-dot arrow lines in Figure 4.3, are the holding arcs of MEP nodes, which enable evacuees to be held at MEPs over time. As the evacuees are represented as uninterrupted flows from MEPs to shelters, holding is not allowed en

route, namely at transshipment nodes. The holding arcs also have an infinite capacity but are associated with a one period arc traverse time. The type (3) arcs, shown with the solid arrow lines in Figure 4.3, are referred as moving arcs, which enable evacuees to enter and leave different spatial nodes at different times. Since currently, the arc traverse times among nodes 1, 2 and 3 are assumed as one period for any arc flow rates, all moving arcs in Figure 4.3 cross one period. The moving arcs are assigned various capacities according to reality.

As discussed before, our evacuation planning problem considers S-curve demand loading pattern and traffic congestion delays to bring about practical evacuation plans. While the S-curve demand loading pattern can be represented with the demand loading arcs, traffic congestion delays can be incorporated with a generalized time-space network, which is applied in the previous research [21, 58].

Figure 4.4: The congestion delay incorporated generalized time-space network

The generalized time-space network, shown in Figure 4.4, is the same as the normal time-space network in Figure 4.3, excepting that more moving arcs are added. As congestion delay results in different arc traverse time for different arc flow rates (amounts), multiple moving arcs (type (3) arcs) are added to each time-expanded node in the gen-

eralized time-space network. For example, the congestion delay incorporated moving arcs of node (1,0), which represents the MEP node 1 at time 0, and node (2,0) are illustrated in Figure 4.4. Except the normal time-space network moving arcs, which cross one period, extra moving arcs crossing two, three, and four periods are shown. A main drawback of the generalized time-space network is its huge size, resulting from a large number of moving arcs. To reduce the number of congestion delay induced moving arcs, the maximum traverse time through each spatial arc can be limited with proper approaches, such as assigning an ultimate arc capacity factor λ for each arc to limit the associated maximum arc traverse time.

According to the generalized time-space network, we can formulate an MIP model (Model (P-L)) to deal with our DFEWS-based dynamic evacuation planning problem. The notations of the model are defined as follows.

Sets

I , set of households in a debris-flow-prone area, indexed by i ,

J , set of MEPs, indexed by j ,

L , set of transshipment points, indexed by l ,

F , set of candidate shelters, indexed by f ,

$T = \{0, 1, 2, \dots, \tau\}$, set of time points, indexed by r, s, t , and u ,

$T^{red} = \{1, 2, \dots, \tau - \kappa - 1\}$, set of candidate time points for red alarm,

N , set of all spatial nodes, indexed by p and q , $N = J \cup L \cup F \cup \{o, e\}$, where o is the super source node and e is the super sink node,

B , set of all real spatial nodes, excluding the super source node and the super sink node,

$B = J \cup L \cup F$,

V , set of all time-space network nodes, indexed by a pair of spatial node index and time point index, like (p, s) and (q, t) ,

A , set of all time-space network arcs, indexed by a pair of time-space network node index, like $((p, s), (q, t))$, or (p, s, q, t) for short.

A^m , set of all real time-space network moving arcs, $(p, s, q, t) \in A$, $p \neq q$, $p \neq o$, $q \neq e$,

A_{qt}^{in} , set of all time-space network arcs $(p, s, q, t) \in A$ that enter time-space network node $(q, t) \in V$,

A_{qt}^{out} , set of all time-space network arcs $(q, t, p, s) \in A$ that leave time-space network node $(q, t) \in V$.

Parameters

σ , weight on the expected en route penalty relative to the planned evacuation clearance time,

M , a large number,

κ , maximum holding periods at MEPs after red alarm,

d_i , evacuation demand of household $i \in I$,

D , evacuation demand of all households, $D = \sum_{i \in I} d_i$,

C_f , capacity of candidate shelter $f \in F$,

P^r , probability that a debris flow disaster occurs at time point $r \in T$,

τ , total planning periods after yellow alarm,

G_{st} , loaded percentage of the total evacuation demand at time point $s \in T$ when the red alarm is given at time point $t \in T^{red}$,

L_{psqt} , lower bound of flow amount on arc $(p, s, q, t) \in A^m$,

U_{psqt} , upper bound of flow amount on arc $(p, s, q, t) \in A^m$,

ρ_{psqt} , penalty factor for unit en route flow on arc $(p, s, q, t) \in A$.

Decision variables

$$x_{ij} = \begin{cases} 1 & \text{if the evacuation demand of household } i \in I \text{ is assigned to MEP } j \in J, \\ 0 & \text{otherwise.} \end{cases}$$

$$h_t = \begin{cases} 1 & \text{if the red alarm is given at time point } t \in T^{red}, \\ 0 & \text{otherwise.} \end{cases}$$

$$v_{psqt} = \begin{cases} 1 & \text{if there is flow on moving arc } (p, s, q, t) \in A^m, \\ 0 & \text{otherwise.} \end{cases}$$

$g_j \geq 0$, total evacuation demand assigned to MEP $j \in J$,

$b_{jst} \geq 0$, loaded evacuation demand at MEP $j \in J$ at time point $s \in T$ when the red alarm is given at time point $t \in T^{red}$,

$z_{psqt} \geq 0$, amount of evacuation flow on arc $(p, s, q, t) \in A$,

$\theta \geq 0$, planned evacuation clearance time.

Model formulation

Based on the notations and the constructed time-space network, the DFEWS-based dynamic evacuation planning problem can be formulated as the following optimization model:

$$(\mathbf{P}\text{-}\mathbf{NL}) \quad \text{Min} \quad \theta + \sigma \sum_{r \in T} \left[P^r \left(\sum_{(p,s,q,t) \in A: q \in J \cup L, s < r, t \geq r} \rho_{psqt} z_{psqt} + \sum_{(p,s,q,t) \in A: q \in F, s < r, t > r} \rho_{psqt} z_{psqt} \right) \right] \quad (4.1)$$

s.t.

$$\sum_{j \in J} x_{ij} = 1, \forall i \in I, \quad (4.2)$$

$$\sum_{i \in I} d_i x_{ij} = g_j, \forall j \in J, \quad (4.3)$$

$$\sum_{t \in T^{red}} h_t = 1, \quad (4.4)$$

$$b_{jst} = g_j G_{st} h_t, \forall j \in J, s \in T, t \in T^{red}, \quad (4.5)$$

$$z_{00js} = \sum_{t \in T^{red}} b_{jst}, \forall j \in J, s \in T, \quad (4.6)$$

$$z_{j,t+\kappa, j,t+\kappa+1} \leq D \cdot (1 - h_t), \forall j \in J, t \in T^{red}, \quad (4.7)$$

$$\sum_{t \in T: (f,t,e,\tau) \in A} z_{fte\tau} \leq C_f, \forall f \in F, \quad (4.8)$$

$$\sum_{(j,t) \in V: (0,0,j,t) \in A} z_{00jt} = \sum_{(p,t) \in V: (p,t,e,\tau) \in A} z_{pte\tau}, \quad (4.9)$$

$$\sum_{(p,s) \in V: (p,s,q,t) \in A_{qt}^{in}} z_{psqt} = \sum_{(p,s) \in V: (q,t,p,s) \in A_{qt}^{out}} z_{qtps}, \forall (q,t) \in V, \quad (4.10)$$

$$z_{psqt} \leq U_{psqt} v_{psqt}, \forall (p,s,q,t) \in A^m, \quad (4.11)$$

$$z_{psqt} \geq L_{psqt} v_{psqt}, \forall (p,s,q,t) \in A^m, \quad (4.12)$$

$$\sum_{r \in T, u \in T: r > s, u < t, (p,r,q,u) \in A^m} v_{prqu} \leq M \cdot (1 - v_{psqt}), \forall (p,s,q,t) \in A^m, \quad (4.13)$$

$$\sum_{t \in T: (p,s,q,t) \in A^m} v_{psqt} \leq 1, \forall (p,s) \in V, q \in B, \quad (4.14)$$

$$\theta \geq t v_{psqt}, \forall (p,s,q,t) \in A^m : q \in F, \quad (4.15)$$

$$x_{ij} \in \{0, 1\}, \forall i \in I, j \in J, \quad (4.16)$$

$$h_t \in \{0, 1\}, \forall t \in T^{red}, \quad (4.17)$$

$$v_{psqt} \in \{0, 1\}, \forall (p, s, q, t) \in A^m, \quad (4.18)$$

$$g_j \geq 0, \forall j \in J, \quad (4.19)$$

$$b_{jst} \geq 0, \forall j \in J, s \in T, t \in T^{red}, \quad (4.20)$$

$$z_{psqt} \geq 0, \forall (p, s, q, t) \in A, \quad (4.21)$$

$$\theta \geq 0. \quad (4.22)$$

The objective function (4.1) minimizes the sum of the planned evacuation clearance time and the weighted expected en route penalty cost. Minimizing the planned evacuation clearance time θ is the primary goal of the evacuation planning. To achieve the secondary goal, the model also minimizes the expected en route penalty cost over all potential disaster occurrence times. The penalty factor ρ_{psqt} of each arc can represent en route life-threatening risk (the arcs inside the debris-flow-prone area are assigned relatively bigger penalty factors to reflect the higher risk of staying there, and the relationship $\rho_{psq(t-1)} \leq \rho_{psqt}, \forall t \in T$ holds to indicate that the more traffic congestion delays, the more en route risk) or other costs (such as social discontent and evacuation panic) associated with not enabling all evacuees to reach shelters before the debris flow disaster. For simplicity, we apply the well-known weighted sum method [120], which assigns a weight factor σ on the secondary goal to aggregate the two sub-objectives into a single objective formulation. The two sub-objective terms, the planned evacuation clearance time and the expected en route penalty cost, have the key relationship that when all evacuees can be cleared before the earliest potential disaster occurrence time, the expected en route penalty cost is zero, and the objective function 4.1 is equivalent to Minimize the planned evacuation clearance time only; otherwise, the expected en route penalty cost is non-zero, and if the weight σ is non-zero, the objective function 4.1 is fully activated. Such relationship makes it unnecessary to normalize the values of time-based and cost-based sub-objectives first. However, we can easily normalize the two

sub-objective terms by dividing them with T and $D \left[\text{Max}_{(p,s,q,t) \in A} (\rho_{psqt}) \right]$, respectively.

Formulation details of the secondary goal are introduced as follows. En route evacuees exist only when a debris flow disaster occurs at a time $r \in T$ that is earlier than the planned evacuation clearance time θ . Specifically, assuming that the debris flow disaster occurs at time r with probability P^r , the total amount of en route flows, which head to an MEP or a transshipment node $q \in J \cup L$ at time r , can be achieved by aggregating the planned evacuation flow amounts z_{psqt} , which leave last node $p \in N$ before time r with $s < r$ and reach the node q at or after time r with $t \geq r$. Similarly, the total amount of en route flows, which head to a shelter node $q \in F$, can be obtained, excepting that the flows, which reach shelter nodes q at time r , are not counted as en route flows. The en route flows are penalized by their corresponding penalty factor ρ_{psqt} .

Constraints (4.2) ensure that the evacuation demand of each household is assigned to an MEP. Constraints (4.3) calculate the total assigned evacuation demand of each MEP. Constraint (4.4) ensures that the red alarm is announced at a time to mobilize compulsory evacuation. Constraints (4.5) define variables b_{jst} , where $G_{st}h_t$ represents the demand loading percentage (following an S-curve distribution) at time point s when the red alarm is given at time point t . Multiplying $G_{st}h_t$ by the total assigned demand g_j of MEP j equals to b_{jst} , the loaded evacuation demand at MEP j at time point s when the red alarm is given at time t . Constraints (4.6) load evacuation demands on time-space network arcs $(o, 0, j, t)$, the demand loading arcs, by aggregating the corresponding variables b_{jst} over all potential red alarm times t . Constraints (4.7) ensure that once the red alarm is given at time t , all left evacuees must leave from their assigned MEP j before time $t + \kappa$, which is equivalent to require all MEPs cannot hold left evacuees from time $t + \kappa$ to time $t + \kappa + 1$. As the total evacuation demand D is a trivial upper bound for variables z_{psqt} , Constraints (4.7) are active only when the red alarm is given at time t with $h_t = 1$. Constraints (4.8) are shelter capacity constraints. Constraints (4.9) ensure that all evacuation demands leave from the super source node $(o, 0)$ and arrive at the super sink node (e, τ) . Constraints (4.10) ensure network flow balance at each time-space node.

Constraints (4.11) and (4.12) are applied to ensure that the flow amount on each moving arc is compatible with the arc traverse time of the arc. The compatible rela-

relationship between flow amount and arc traverse time is decided by VDFs, which are introduced in Chapter 2, to approximate traffic congestion delays. In addition, Constraints (4.11) and (4.12) together define the flow indicator variables v_{psqt} for all moving arcs. As $U_{psqt} > 0, L_{psqt} > 0, U_{psqt} > L_{psqt}, \forall (p, s, q, t) \in A^m$, if there is flow on a moving arc $(p, s, q, t) \in A^m$ with $z_{psqt} > 0$, then v_{psqt} must be 1 according to Constraints (4.11), which also activates the flow amount constraints $L_{psqt} \leq z_{psqt} \leq U_{psqt}, \forall (p, s, q, t) \in A^m$. However, if there is no flow on a moving arc (p, s, q, t) with $z_{psqt} = 0$, then v_{psqt} must be 0 according to Constraints (4.12).

Moreover, Constraints (4.13) and (4.14) ensure that two logical rules are followed by moving-arc flows. Constraints (4.13) make sure that the moving-arc flows obey the first-in-first-out (FIFO) rule, that is, once there is a flow leaving spatial node p at time s and reaching spatial node q at time t , no flows are allowed to leave the same spatial node p after time s but reach the same spatial node q before time t . Due to the large number M , if there is no flow on a moving arc (p, s, q, t) with $v_{psqt} = 0$, the corresponding constraint (4.13) of that moving arc is trivial. However, once there is a flow on the moving arc (p, s, q, t) with $v_{psqt} = 1$, the right hand side of that moving arc's constraint (4.13) becomes 0, which activates the FIFO rule. Constraints (4.14) realize the one-travel-time rule, which ensures that at most one of the multiple congestion-delay-induced moving arcs (the moving arcs leaving from a same spatial node at the same time and reaching another identical spatial node at different times) can take a flow.

The effects of the two logical rules, which are ensured by Constraints (4.13) and (4.14), are illustrated with Figure 4.5. All moving arcs between the MEP node 1 and

Figure 4.5: Illustration of the effects of logical rules for moving arc flows

the transshipment node 2 over 4 periods are shown in the figure. It is assumed that there

is a flow on the moving arc (1,0,2,4), which is represented with the bold solid arrow line. Then, Constraints (4.13) ensure that arcs (1,1,2,2), (1,1,2,3), and (1,2,2,3), shown with the dashed arrow lines, cannot take flows so as to obey the FIFO rule. Moreover, Constraints (4.14) ensure that arcs (1,0,2,1), (1,0,2,2), and (1,0,2,3), as shown with the dash-dot arrow lines, cannot carry flows based on the one-travel-time rule.

Constraints (4.15) and objective function (4.1) together define the planned evacuation clearance time θ . Constraints (4.15) ensure that the evacuation clearance time θ is later than or equal to any time t that there is flow reaching any shelter node $q \in F$ with $v_{psqt} = 1$. Thus, the minimal θ as required by the objective function that satisfies Constraints (4.15) is the planned evacuation clearance time. Finally, Constraints (4.16)-(4.22) define the binary or positive continuous bounds for the various decision variables.

Due to the multiplication of the continuous variable g_j and the binary variable h_t , Constraints (4.5) have “0-1” quadratic terms, which turns Model (**P-NL**) into a mixed-integer quadratically constrained programming model. However, as the continuous variables g_j are trivially bounded by 0 and the total evacuation demand D , we can apply a famous trick [46] to replace the “0-1” quadratic constraints with the following linear constraints:

$$b_{jst} \geq 0, \forall j \in J, s \in T, t \in T^{red}, \quad (4.23)$$

$$b_{jst} \leq DG_{st}h_t, \forall j \in J, s \in T, t \in T^{red}, \quad (4.24)$$

$$b_{jst} \leq g_jG_{st}, \forall j \in J, s \in T, t \in T^{red}, \quad (4.25)$$

$$b_{jst} \geq g_jG_{st} - D(1 - h_t)G_{st}, \forall j \in J, s \in T, t \in T^{red}. \quad (4.26)$$

After replacement, our proposed MIP Model (**P-L**) for the DFEWS-based dynamic evacuation planning problem is formulated as follows:

(**P-L**) Min $\theta +$

$$\sigma \sum_{r \in T} \left[P^r \left(\sum_{(p,s,q,t) \in A: q \in J \cup L, s < r, t \geq r} \rho_{psqt} z_{psqt} + \sum_{(p,s,q,t) \in A: q \in F, s < r, t > r} \rho_{psqt} z_{psqt} \right) \right]$$

subject to (4.2)-(4.4), (4.6)-(4.22), and (4.24)-(4.26).

Constraints (4.23) are left out as they are the same as Constraints (4.20). In model (**P-L**), all evacuation decisions are made before knowing the actual debris flow occurrence time. Particularly, the decisions of the household assignment x_{ij} , the red alarm time h_t , and the routing of evacuation flows z_{psqt} , constitute the three key components of the evacuation planning problem. Essentially, our proposed Model (**P-L**) is a variation of the quickest flow model with complicating constraints and variables as well as multiple objectives.

4.3 Illustrative Case Study

We conduct an illustrative case study to verify the effectiveness of our proposed Model (**P-L**). We also carry out sensitivity analyses on some key parameters to generate managerial insights and policy suggestions for developing better evacuation plans.

4.3.1 Parameter Setting

The illustrative evacuation case is based on the spatial network shown in Figure 4.6. According to the network, the debris-flow-prone area has three MEPs (nodes 1-3) to load the evacuation demand of each household. Nodes 4-6 represent the main transshipment points of the evacuation network, and nodes 7-10 are the candidate shelters. The 10 solid arrow lines represent the main evacuation roads and go from the MEPs to the candidate shelters. Each MEP node has a holding arc pointing to itself to enable evacuees to be temporarily held there. The other dummy arcs (dashed arrow lines) enable all evacuation demands to origin from the super source node o and to finally arrive at the super sink node e .

It is assumed that a total of 100 households located in the debris-flow-prone area. The evacuation demand d_i of each household $i \in I$ is a randomly generated integer ranging from 1 to 40 passenger-car units (PCUs), and the total evacuation demand D of all households, which is 2009 PCUs, is less than the total available capacity of all candidate shelters, which is 2200 PCUs, in the case. Specifically, the available capacities C_f of the

Figure 4.6: The spatial network of the illustrative case study

shelter nodes 7, 8, 9, and 10 are set as 300, 400, 600, and 900 PCUs, respectively.

The evacuation planning horizon of the area is set to 12 hours, which is further discretized into 48 periods ($\tau = 48$) with each period 15 minutes. Although discretizing the 12 hours into more periods can increase the precision of the evacuation plan, the size and difficulty of the problem also increase significantly. The estimated potential disaster occurrence time r and the associated probabilities P^r are listed in Table 4.1. According to the table, a debris flow disaster may occur between time periods 28 and 37, that is, about 7 to 9 hours after the yellow alarm, with a probability of 87%.

Table 4.1: Estimated probability distribution of the disaster occurrence time

Time point r	0-27	28	29	30	31	32	33	34	35	36	37	38-48
Probability P^r	0	0.03	0.06	0.08	0.1	0.18	0.14	0.11	0.09	0.06	0.02	0

The parameters of the spatial arcs are listed in the Table A3 of Appendix A. In general, the 10 solid-arrow-line arcs are categorized into three types according to their represented road conditions. It is assumed that the practical capacity values (c_{pq}) of the type 1, type 2, and type 3 arcs are 15, 20, and 30 PCUs per period, respectively. The ultimate capacity factor λ is set to 2, indicating that the maximum flow rates that can be held on the evacuation arcs are twice their practical capacities. In the case, we assume that the en route penalty factors $\rho_{psqt}, \forall (p, s, q, t) \in A$ are static. Thus, parameters ρ_{pq} are given in Table A3. The arcs closer to the shelters are assigned a relatively small penalty value, which represents that the closer to the shelters, the fewer disaster occurrence impacts to the en route evacuees. The weight factor σ for the expected en route penalty cost is set to 1. The parameter κ is set to 2 to ensure that all left evacuees will wait at

most two periods (30 minutes) at MEPs after the red alarm.

Since our dynamic evacuation planning problem is based on a discrete-time setting, step functions are applied in our Model (P-L) to approximate the flow-time relationship of traffic congestion delays. In the case study, we produce the step function parameters L_{psqt} and U_{psqt} for all time-space network moving arcs $(p, s, q, t) \in A^m$ according to the corresponding spatial arc parameters (practical capacity c_{pq} and free flow time t_{pq}^0) in Table A3 and the famous BPR function [110]. Details about the BPR function are introduced in Chapter 2. For the illustrative purpose, we also let the BPR coefficients α equal to 0.15 and β equal to 4 for all spatial arcs.

The procedure of producing the step function parameters L_{psqt} and U_{psqt} is illustrated with Figure 4.7. First, for each spatial arc (p, q) , the arc flow rates (the $x(1)$, $x(2)$, and $x(3)$ points on x-axis in Figure 4.7), which lead to the jumping of the integer arc traverse time, are achieved with the inverse BPR function

$$x_{pq}(t_{pq}) = c_{pq} \sqrt[\beta]{\frac{t_{pq}/t_{pq}^0 - 1}{\alpha}}$$

by letting the arc traverse time t_{pq} equal to the possible integer value such that $t_{pq}^0 \leq t_{pq} \leq \left\lceil t_{pq}^0 \cdot (1 + \alpha \lambda^\beta) \right\rceil$ in sequence. Then, the step function parameters L_{psqt} and U_{psqt} (in unit of flow amount) are obtained with $x_{pq}(t - s - 1) \cdot (t - s)$ and $x_{pq}(t - s) \cdot (t - s)$, respectively, where $x_{pq}(\cdot)$ represent jumping flow rates and $(t - s)$ is the arc traverse time. It should be noted that all L_{psqt} are strictly greater than 0. Furthermore, as the maximum arc flow rates are bounded by the ultimate capacities λc_{pq} , the parameters U_{psqt} are also bounded by ultimate arc flow amounts, which are $\left\lceil t_{pq}^0 \cdot (1 + \alpha \lambda^\beta) \right\rceil \lambda c_{pq}$.

Based on the spatial network of Figure 4.6 and the possible arc traverse times of each spatial arc, the time-space network of the illustrative case can be easily constructed. The time-space network is similar to the one in Figure 4.4, excepting that more arcs and nodes are included in the case study network.

The parameters G_{st} , which approximate the S-curve evacuation demand loading pattern after the yellow alarm, are produced based on the Rayleigh distribution approach

Figure 4.7: Illustration of the discretized step function of the BPR function

applied by Tweedie *et al.* [107]. The approach is simple and exogenous to the evacuation arrangements, with only one tuning coefficient $\pi > 0$ to describe the estimated S-curve demand loading pattern. The Rayleigh distribution is shown as follows:

$$F(t) = \begin{cases} 1 - e^{-\pi t^2} & \text{if } t \geq 0, \\ 0 & \text{if } t < 0, \end{cases} \quad \forall t \in T,$$

where $F(t)$ denotes the cumulative distribution of the loaded percentage of total evacuation demand until time t . As shown in Figure 4.8, the larger π , the faster the demands is loaded. In the illustrative case, π is set to 0.003. The resulting S-curve loading pattern, as shown in Figure 4.8, indicates that about 80% of the total evacuation demand is loaded at MEPs after 24 periods (*i.e.*, 6 hours).

Given $F(t)$ and $\pi = 0.003$, the parameters G_{st} , the loaded percentage of the total demand at time $s \in T$ when the red alarm is given at time $t \in T^{red}$, are generated with

Figure 4.8: Illustration of S-curved Rayleigh distributions

the following equations,

$$G_{st} = \begin{cases} F(s) - F(s-1) & \text{if } 1 \leq s \leq t + \kappa - 1, \\ 1 - F(s-1) & \text{if } s = t + \kappa, \\ 0 & \text{if } s > t + \kappa \text{ or } s = 0, \end{cases} \quad \forall s \in T, t \in T^{red}.$$

The equations of G_{st} are based on two assumptions. First, all evacuation demand of the t th ($t \geq 1$) period is loaded at time point t . Second, once the red alarm is given at time t , all left evacuation demand is loaded at time point $t + \kappa$. As the S-curve evacuation demand loading pattern can be influenced by specific natural and social conditions, it varies from place to place. Therefore, it is significant to conduct detailed social and field investigations to derive and apply a proper S-curve distribution $F(t)$ in practice.

4.3.2 Results and Insights

Base case solution

For the illustrative case, Model (P-L) has 33,181 constraints and 12,017 decision variables (2,628 binary variables), and it is directly solved with the commercial MIP solver

GUROBI on a laptop with the 64-bit Windows 10, 8G memory, and Intel Core i7-4500U@1.80GHz CPU. The case is optimally solved with 115 seconds and the results are shown in Table 4.2.

Table 4.2: Solution of the illustrative case

Objective value	143.24
Evacuation clearance time	32
Weighted expected penalty	111.24
Expected penalty	111.24
Red alarm time	17
Demand assignments of each MEP	
Node 1	285
Node 2	1296
Node 3	428
Served demands (arrival times) at each shelter	
Node 7	300 (20,22-25,28-31)
Node 8	400 (21,23,24,26,28,29,31)
Node 9	600 (19,21,27,29,30,32)
Node 10	709 (10,12,14-16,18,19,21,22,24,28,30,32)
Time (s)	115

As the planned evacuation clearance time 32 is later than the earliest potential disaster occurrence time 28, the expected en route penalty cost of 111.24 is caused. Most of the household demand is assigned to MEP node 2 since the MEP is connected with transshipment nodes 4 and 5 so that it has more transportation resources and flexibility to arrange the evacuation flows. Except shelter node 10, the capacities of the other three candidate shelters (nodes 7, 8, and 9) are fully utilized since the three shelters are closer to the MEPs. Moreover, it is found that the first arriving flow of shelter node 10 is significantly earlier than those of the other three shelter nodes. This indicates that the earlier voluntary evacuees are all guided to the farther shelter node 10 so as to save the capacities of nearer shelters for late evacuees. Although the arrangement is unfair to the early voluntary evacuees, it benefits the entire system for achieving an early evacuation clearance time.

The first and the last evacuation flows from MEP nodes 1, 2, and 3 are illustrated in Figures 4.9, 4.10, and 4.11, respectively.

Figure 4.9: Illustration of the first and last flows from MEP node 1

Figure 4.10: Illustration of the first and last flows from MEP node 2

Figure 4.11: Illustration of the first and last flows from MEP node 3

In general, the first voluntary evacuation flows from the three MEPs are all guided to MEP node 10 and their evacuation times are all 9 periods. However, after the red alarm, which is given at time 17, the last compulsory evacuation flows (leaving MEPs at time 19) from MEP 2 and MEP 3 take longer evacuation times to reach shelters. Specifically, the last evacuation flows from MEP 2 and MEP 3 take 12-13 periods and 10-11 periods to reach the four shelters, respectively. The increased evacuation time is due to traffic congestion delays, which however is the inevitable price of reducing the expected en route penalty cost.

Benefits of considering traffic congestion and applying the staging strategy

In previous dynamic evacuation planning models, traffic congestion delays and the evacuation staging strategy are seldom considered. However, the illustrative case study shows the benefits of considering these two factors.

To show the benefits of incorporating traffic congestion delays in our planning model, a comparison MIP Model (**CP-L**), which ignores the flow-time relationship of traffic congestion delays, is constructed. Model (**CP-L**) is based on a normal time-space network (similar to the one in Figure 4.3) without congestion-delay moving arcs, and it has

the following formulation:

$$(\mathbf{CP-L}) \quad \text{Min} \quad \theta + \sigma \sum_{r \in T} \left[P^r \left(\sum_{(p,s,q,t) \in A: q \in J \cup L, s < r, t \geq r} \rho_{psqt} z_{psqt} + \sum_{(p,s,q,t) \in A: q \in F, s < r, t > r} \rho_{psqt} z_{psqt} \right) \right] \quad (4.27)$$

s.t.

$$(4.2)-(4.4), (4.6-4.10), (4.16)-(4.17), (4.19)-(4.22), (4.24)-(4.26),$$

$$z_{psqt} \leq (t - s) \cdot \lambda c_{pq}, \forall (p, s, q, t) \in A^m, \quad (4.28)$$

$$z_{psqt} \leq M w_t, \forall (p, s, q, t) \in A^m : q \in F, \quad (4.29)$$

$$\theta \geq t \cdot w_t, \forall t \in T, \quad (4.30)$$

$$w_t \in \{0, 1\}, \forall t \in T. \quad (4.31)$$

There are two major differences between Model **(CP-L)** and Model **(P-L)**. First, each moving arc is associated with an ultimate capacity constraint (4.28) in Model **(CP-L)** rather than the step function constraints (4.11) and (4.12) in Model **(P-L)**. Second, without congestion-delay moving arcs, Model **(CP-L)** drops the binary flow indicator variables v_{psqt} and some constraints (that is, Constraints (4.13)-(4.15) in Model **(P-L)**). To define the evacuation finish time θ in Model **(CP-L)**, Constraints (4.29)-(4.31) are added. In all, without considering traffic congestion delays, Model **(CP-L)** has significantly fewer binary decision variables and constraints than those of Model **(P-L)**.

With the illustrative case inputs, Model **(CP-L)** is optimally solved by GUROBI solver as well, and the solutions of Model **(P-L)** and **(CP-L)** are compared in the left two columns (Columns of Model **(P-L)** and Model **(CP-L)**) of Table 4.3.

As shown in Table 4.3, the solutions of the two models are different, and Model **(CP-L)** produces a worse plan. The differences are due to the observation that in the case, the ultimate capacity constraints (4.28) of Model **(CP-L)** are tighter than the step function constraints (4.11) and (4.12) of Model **(P-L)**, which can be seen from comparing the constraint parameters. Such tighter constraints lead Model **(CP-L)** to underutilize transportation capacities and to achieve a longer evacuation clearance time. However, in

Table 4.3: Solution comparison between Models **(P-L)** and **(CP-L)**

	Model (P-L)	Model (CP-L)	Model (P-L) -m	Model (CP-L) -m
Objective value	143.24	384.33	11	11
Evacuation clearance time	32	35	11	11
Weighted expected penalty	111.24	349.33	0	0
Expected penalty	111.24	349.33	0	0
Red alarm time	17	24	1	1
Time (s)	115	18	4	4

other cases, the constraints of Model **(CP-L)** can be more relaxed to overutilize transportation capacities to bring about seemingly better evacuation plans which suffer from serious traffic congestion delays in reality. In all, the comparison proves that our Model **(P-L)** contributes to utilizing limited transportation capacities properly and producing better evacuation plans for field practice at traffic congestion expected areas.

However, Model **(CP-L)** has its merits. Essentially, Model **(CP-L)** is a special case (a simplified version) of our proposed Model **(P-L)**. If a planning area has sufficient transportation capacity to avoid traffic congestion delays during evacuation, Model **(CP-L)** can be applied to achieve the same solution of Model **(P-L)**, but with less solving resources and efforts. For example, if modifying the practical capacities c_{pq} of all spatial arcs as 10 times their base case values, Model **(CP-L)** and **(P-L)** achieve the same solutions, which are shown in the right two columns (Columns of Model **(P-L)**-m and Model **(CP-L)**-m) of Table 4.3. In general, when traffic congestion delays are not an expected problem during evacuation, applying Model **(CP-L)** is a better choice as it leads to comparatively higher problem-solving efficiency.

Model **(P-L)** is based on a time-space network that implements the staging strategy with holding arcs. The benefits of the staging strategy are highlighted in Table 4.4, which shows that implementing the staging strategy at MEPs contributes to achieving a better evacuation plan. In addition, by repeating the comparison in Table 4.4 with other cases, which are listed in Table 4.11, we find that staging is another effective approach, besides routing, to reduce traffic congestion delays during evacuation. Although loaded evacuees can start their evacuations from MEPs earlier without staging, the traffic congestion delays due to converged evacuation demands can lead to much longer travel time and

bring about more adverse impacts to en route evacuees.

Table 4.4: Comparison between planning with and without the staging strategy

	With staging	Without staging
Objective value	143.24	580.94
Evacuation clearance time	32	38
Weighted expected penalty	111.24	542.94
Expected penalty	111.24	542.94
Red alarm time	17	24
Time (s)	115	47

Sensitivity analysis on the weight factor of the en route penalty

The weighting method is applied to combine our two sub-objectives and to formulate the objective function of Model (**P-L**). To exam the impacts of the weight factor σ on the optimal plan, sensitivity analysis on σ is conducted and the results are shown in Table 4.5.

Table 4.5: Sensitivity analysis on the weight factor σ

Parameter σ	0	0.1	1	10
Objective value	32	43.12	143.24	1144.44
Evacuation clearance time	32	32	32	32
Weighted expected penalty	0	11.12	111.24	1112.4
Expected penalty	197.76	111.24	111.24	111.24
Red alarm time	18	17	17	17

Table 4.5 indicates that varying the weight factor from its base case value 1 (highlighted with a bold character) to 0.1 or 10 has no impacts on the produced optimal plans. The different objective values are completely due to the value of σ . However, the case of $\sigma = 0$ produces a worse plan with a higher expected penalty (197.76) even though the evacuation clearance time is the same as that in the base case plan. The results show that a positive value of σ enables the model to generate a plan with the least expected en route penalty when such penalty cost is inevitable. Thus, the practical range of parameter σ is $\sigma > 0$ in the base case. Our base case setting of the simplified en route penalty parameters ρ_{pq} , which are typical in real-world cases, essentially avoids contra-

dictions between the two sub-objectives. Thus, any positive value of σ leads to the same evacuation plan.

Policy suggestions on producing safe (no-penalty) evacuation plans

In general, a government hopes to achieve a safe evacuation plan, which ensures that all evacuees can reach candidate shelters before the earliest potential disaster occurrence time without causing any expected en route penalty. With sensitivity analyses on some key parameters, three policy suggestions are provided to turn a dangerous (penalty-existing) evacuation plan into a safe (no-penalty) evacuation plan.

1. Policy of increasing arc capacity

Due to the limited capacities of main evacuation roads, the resulting optimal evacuation plan can have a long duration and cause a high expected penalty. Therefore, a natural solution to produce a better evacuation plan is setting up policies to increase the capacities of certain evacuation roads after the yellow or red alarm. Such capacity increasing policies may include restricting the transportation of non-evacuation vehicles, ensuring one-way transportation on some roads, or other traffic control measures. The impacts of increasing the practical arc capacities of type 1, type 2, and type 3 arcs are shown in Tables 4.6, 4.7, and 4.8, respectively.

Table 4.6: Impacts of increasing the practical capacity of type 1 arcs

Parameter c_{pq} of type 1 arcs	15	20	30	60
Objective value	143.24	57.56	25	20
Evacuation clearance time	32	30	25	20
Weighted expected penalty	111.24	27.56	0	0
Expected penalty	111.24	27.56	0	0
Red alarm time	17	15	6	1
Demand assignment of MEPs				
Node 1	285	314	232	333
Node 2	1296	1280	1458	989
Node 3	428	415	319	687

With the increase of arc practical capacities, the objective value, the evacuation clearance time, and the expected penalty all decrease, but to a limit. Except type 2 arcs, the increase of practical capacities also changes the demand assignments of MEPs and the

Table 4.7: Impacts of increasing the practical capacity of type 2 arcs

Parameter c_{pq} of type 2 arcs	20	30	40	80
Objective value	143.24	124.43	118.47	108.60
Evacuation clearance time	32	31	31	31
Weighted expected penalty	111.24	93.43	87.47	77.60
Expected penalty	111.24	93.43	87.47	77.60
Red alarm time	17	17	17	17
Demand assignment of MEPs				
Node 1	285	285	285	285
Node 2	1296	1296	1296	1296
Node 3	428	428	428	428

Table 4.8: Impacts of increasing the practical capacity of type 3 arcs

Parameter c_{pq} of type 3 arcs	30	45	60	120
Objective value	143.24	131.97	103.74	103.74
Evacuation clearance time	32	32	31	31
Weighted expected penalty	111.24	99.97	72.74	72.74
Expected penalty	111.24	99.97	72.74	72.74
Red alarm time	17	17	16	16
Demand assignment of MEPs				
Node 1	285	285	258	246
Node 2	1296	1296	1391	1397
Node 3	428	428	360	366

red alarm time. It is worth noting that in the illustrative case, the benefits of increasing the same amount of practical capacity are significantly different for the three types of arcs. Specifically, doubling the capacity of all type 1 arcs can bring about most benefits, which enable the evacuation clearance time to decrease from 32 to 25 and the expected penalty to decrease from 111.24 to 0. This indicates that the type 1 arcs are the bottlenecks or key arcs, which deserve prioritized capacity increasing in order to enhance evacuation plans. Moreover, we observe that the red alarm time is non-increasing with the arc capacities increase in Tables 4.6, 4.7, and 4.8. It follows the logic that the more available evacuation arc capacities, the less en route traffic congestion delays, which may contribute to an earlier red alarm to load and evacuate a larger amount of the red alarm induced compulsory evacuation demands for achieving a better plan. On the other hand, if the red alarm time increases with the arc capacities increase, the compulsory evacuation demands become less, and the arc capacities are underutilized especially for the compulsory evacuation, which leads to a worse plan.

In all, establishing proper policies in advance to increase the practical capacities of certain roads is an effective measure to produce safe evacuation plans. Moreover, for the sake of saving traffic control resources and bringing about most benefits, the government should identify the most valuable capacity-increasing arcs through sensitivity analyses.

2. Policy of increasing the maximum holding periods

Increasing the maximum holding periods after the red alarm essentially provides the government more flexibility in dispersing compulsory evacuation demands and reducing the associated congestion delays after the red alarm. Thus, a safe evacuation plan can be achieved with the policy.

As shown in Table 4.9, with the increase of the parameter κ , the evacuation plans become better in terms of the achieved objective value. When $\kappa \geq 5$, the evacuation ends with the shortest time (18 periods) and the red alarm is given at time 1. However, the evacuation plans of $\kappa \geq 5$ are impractical, and they may cause serious social problems. On one hand, giving red alarm at time 1 nullify the yellow alarm mobilization mechanism. On the other hand, it is unreasonable to hold evacuees at MEPs for a long time after the compulsory evacuation order. It seems that setting κ to 3 (45 minutes)

instead of 2 is a satisfactory choice for the illustrative case, as the resulting evacuation plan not only becomes safe but also provides a relatively long duration (12 periods) for voluntary evacuation. Moreover, holding the evacuees at most 45 minutes (15 minutes more than the base case setting) after the red alarm looks like an acceptable change to both evacuees and governments.

Table 4.9: Impacts of increasing the maximum holding periods after the red alarm

Parameter κ	1	2	3	4	5	6
Objective value	541.99	143.24	28	24	18	18
Evacuation clearance time	37	32	28	24	18	18
Weighted expected penalty	504.99	111.24	0	0	0	0
Expected penalty	504.99	111.24	0	0	0	0
Red alarm time	24	17	12	7	1	1

In fact, the parameter κ should be decided for each planning area specifically. Although a bigger value of κ always contributes to a lower objective value, it can lead to an impractical plan, which is unacceptable to the evacuees and governments. The sensitivity analysis on κ is significant to apply the policy of increasing the maximum holding periods in field practice. In extreme cases where the red alarm must be given at time 1 and evacuees must wait a long time after the red alarm, the government should keep smooth communications with the evacuees to reduce their dissatisfaction and anxiety.

3. Policy of encouraging more active voluntary evacuation

Setting up a policy to encourage more active voluntary evacuation after the yellow alarm is another approach to produce safe evacuation plans. As we approximate the S-curve voluntary evacuation demand loading pattern with the Rayleigh distribution, a sensitivity analysis on the Rayleigh distribution parameter π is conducted and the results are shown in Table 4.10.

As mentioned before, a higher value of π indicates a more active voluntary evacuation behavior of evacuees. In Table 4.10, with the increase of π , the optimal objective value decreases, but to the limit of 17. Particularly, if the S-curve demand loading pattern can be adjusted to follow the trends of $\pi = 0.006$ or $\pi = 0.01$ rather than the trend of the base case value, $\pi = 0.003$, the evacuation can be finished earlier without expected penalty. When $\pi = 0.001$, Model (P) is infeasible as there is nearly no voluntary evac-

Table 4.10: Impacts of adjusting the S-curve demand loading pattern after the yellow alarm

Parameter π	0.001	0.003	0.004	0.006	0.01	0.1	0.2
Objective value	Infeasible	143.24	34.2	27	24	17	17
Evacuation clearance time	-	32	29	27	24	17	17
Weighted expected penalty	-	111.24	5.2	0	0	0	0
Expected penalty	-	111.24	5.2	0	0	0	0
Red alarm time	-	17	15	13	13	8	8

uation. Hence, the compulsory evacuation demand is too large to be feasibly planned within the step function bounds of all moving arcs. Facing that infeasible scenario, the government must encourage the evacuees to conduct more active voluntary evacuation or apply the two policies mentioned before to generate a feasible plan. Additionally, in the special case where the voluntary evacuation is very active, like the trend of $\pi = 0.2$, the government can also suggest a less active voluntary evacuation, like the trend of $\pi = 0.1$, to reduce congestion and unnecessary holding at MEPs without increasing the evacuation clearance time.

For field practice, we suggest the three policies with different priorities to turn a dangerous plan into a safe one. As increasing the maximum holding periods after the red alarm is just a planning policy change, which costs nearly nothing, the policy should be the first choice, as long as the increased holding time is still acceptable to evacuees and governments and the resulting plan is still practical and reasonable. We believe that the capacity increasing policy ranks second as it is relatively easier for a government to practice. Encouraging more active voluntary evacuation is suggested as a last resort considering its implementation difficulties in reality. Modifying the voluntary evacuation behavior of evacuees is against the natural will of evacuees, and its success greatly depends on the huge input of social education and the close cooperation of evacuees.

4.4 Challenge of Solving Model (P-L)

To find insights about the challenge of solving Model (P-L), we conduct a numerical experiment, which solves different-size cases and compares their solution qualities in

Table 4.11.

Table 4.11: Solution quality comparison of different cases

Case	1 (base case)	2	3	4	5
Nodes	10	10	15	10	20
Arcs	10	10	20	10	30
Households	100	1000	1000	1000	1000
Periods	48	48	48	96	96
Constraints	33,181	34,081	61,920	109,489	254,938
Variables	12,017 (2,628)	14,717 (5,328)	25,950 (9,617)	40,781 (7,920)	91,313 (20,718)
Time (s)	115	136	1,551	2,426	26,700
Gap	0	0	0	0	0

From Case 1 (our illustrative case) to Case 5, the problem sizes, which in terms of the constraint and variable numbers (numbers of continuous and binary variables are listed outside and inside brackets, respectively), become increasingly large, and it takes increasingly more time for the MIP solver GUROBI to achieve the optimal solutions. However, the quantity changes of households, nodes and arcs, and periods have different impacts on the optimal solution time. While the number of periods influences the solution time most (shown by comparing Cases 2 and 4), the solution time influences of the numbers of nodes and arcs and households rank second (shown by comparing Cases 2 and 3) and third (shown by comparing Cases 2 and 1), respectively. Moreover, the problems size and solution time comparison of Cases 1 and 5 highlights the importance and necessity of developing efficient solution strategies for solving medium- and large-size cases of our Model (**P-L**).

4.5 Application Benefits of Model (**P-L**)

Deciding a proper CRT value for each debris-flow-prone area is the key in the DFEWS of Taiwan. Since the evacuation clearance time is not explicitly considered in the system, issuing the yellow alarm (red alarm) purely based on the relationship between FCR (ACR) and CRT can be misleading and ineffective. As a supplement, our Model (**P-L**) enables the planner to have a better evaluation of the planned evacuation duration and the expected en route penalty. In sum, Model (**P-L**) can be applied in field practice to

support the DFEWS of Taiwan in the following aspects.

First, Model (**P-L**) aids in increasing the evacuation preparations of evacuees and governments. As the MEP assignment of each household is announced in advance and the government controls the entire evacuation plan, including the red alarm time after yellow alarm and the routing of evacuation flows, before potential debris flow disasters, the preparations of the evacuees and the government are both improved.

Second, Model (**P-L**) makes the evacuation management work of the government easier. Unlike DFEWSs, which commonly decide the mobilization order time based on the exogenous rainfall data, Model (**P-L**) decides the red alarm (compulsory evacuation order) time endogenously with the goal of achieving an early evacuation clearance time. With the help of Model (**P-L**), the government not only knows when to give the red alarm once the yellow alarm is issued but also knows potential evacuation problems in advance. Based on the DFEWS of Taiwan, once the actual rainfall data indicate that the red alarm should be announced earlier than the planned time, the government should follow the DFEWS and be fully prepared for decreasing traffic congestion delays. On the contrary, if the DFEWS indicates that the red alarm time is later than the planned time, the government should conservatively follow the planned red alarm time for ensuring the safety of evacuees and for achieving a short evacuation clearance time.

Third, Model (**P-L**) enables the yellow alarm (voluntary evacuation order) time to be safely delayed to avoid initializing voluntary evacuations too early. This is based on the solutions of Model (**P-L**) and the estimated earliest potential disaster occurrence time. For example, if the planned evacuation only requires 10 periods to finish and the estimated earliest potential disaster occurrence time is at time 30, it makes no sense to follow the DFEWS to give the yellow alarm right at the time that FCR exceeds CRT (the time 0 of our planning horizon). Instead, following the planning result, the government can safely delay the yellow alarm for a maximum of 20 periods, and still ensure that all evacuees reach candidate shelters before the earliest potential disaster occurrence time 30. The ability of safely delaying the voluntary evacuation order time is precious for governments and victims since it provides flexibility and possibility to avoid an unnecessary evacuation, which is significant in a case that the rainfall situation and the disaster

occurrence probability can unexpectedly change.

Forth, Model (**P-L**) supports the government to design, evaluate, and implement proper evacuation enhancement policies in advance to produce safe evacuation plans. If the evacuation plan has the expected en route penalty, indicating that the disaster may occur before all evacuees reach shelters, the government can implement the suggested three policies to turn the dangerous plan into a safe one. Without Model (**P-L**), it is difficult for the government to evaluate the necessity of implementing certain policies for each disaster prone area.

Fifth, Model (**P-L**) aids in achieving the goal of protecting human lives better. Model (**P-L**) can take the potential time when ACR exceeds CRT as the potential disaster occurrence time. By doing so, the evacuation plan of Model (**P-L**) is more conservative than the DFEWS of Taiwan, which just issues a red alarm when ACR exceeds CRT. Essentially, following a safe evacuation plan of Model (**P-L**) enables all evacuees to arrive at shelters before the earliest potential red alarm time provided by the DFEWS of Taiwan. Due to the conservative estimation of disaster occurrence time in Model (**P-L**), human lives are better protected.

Last but not the least, our Model (**P-L**) can be easily applied in evacuation planning for other predictable disasters, like hurricanes and floods, as long as a similar early warning system that issues voluntary and compulsory evacuation orders, is implemented to mobilize evacuees. Particularly, we believe that Model (**P-L**) can be applied to greatly accelerate a state-level hurricane evacuation, which is commonly confronted with serious traffic congestion delays.

4.6 Summary of the Chapter

In this chapter, the DFEWS-based dynamic evacuation planning problem is addressed with our proposed Model (**P-L**). The model not only integrates the three common evacuation strategies (mobilization, staging, and routing) but also considers S-curve evacuation demand loading patterns and traffic congestion delays with a generalized time-space network and a step function resulting from a VDF.

An illustrative case study is conducted to show the benefits of Model (**P-L**), to generate managerial insights, and to develop policy suggestions on achieving a safe evacuation plan. First, the routing plan of the case indicates that early voluntary evacuees should be directed to farther shelters to benefit the entire evacuation process. Second, we develop a comparison model, Model (**CP-L**), to show the benefits of explicitly considering traffic congestion delays in the evacuation planning process. The comparison not only shows that Model (**P-L**) contributes to the better utilization of limited transportation capacities but also indicates that Model (**CP-L**) is a better choice for areas without traffic congestion delays during evacuations. Third, it is shown that the staging strategy is an effective strategy for reducing en route traffic congestion delays through dispersing converged evacuation demands from starting points (MEPs) over time. Forth, with sensitivity analyses, three policies (increasing the maximum holding periods, increasing arc capacities, and encouraging more active voluntary evacuation) are proposed for turning a dangerous (penalty-exiting) evacuation plan into a safe (no-penalty) one. Finally, the solving challenge and the application benefits of Model (**CP-L**) are discussed, and we point out that Model (**CP-L**) can be applied in evacuation planning for other predictable disasters as long as a similar early warning system is implemented to mobilize evacuees.

In all, the chapter provides a novel model, Model (**CP-L**), to deal with the DFEWS-based dynamic evacuation planning problem for debris-flow-prone areas where traffic congestion delays are expected. With the help of the model, more effective and efficient evacuation plans can be produced in advance, which benefit both evacuees and governments in field practice.

Chapter 5

Conclusions and Future Work

5.1 Summary of the Thesis

EL is the key to alleviate disaster impacts and to accelerate pre- and post-disaster operations. Particularly, the plannings of emergency supply and evacuation serve a fundamental role to increase the effectiveness and efficiency of EL in field practice. To facilitate the plannings, substantial research efforts have been put into this field and various planning models have been developed in the past few decades. However, the application challenges of building more practical planning models, which incorporate realistic factors and relationships in the planning process, for enhancing the performances of field applications still exist. As traffic congestion phenomena commonly exist under emergency situations, the thesis focuses on developing more realistic EL planning models, which explicitly incorporate traffic congestion delays.

In Chapter 1, a general introduction of the two principal terms, emergency logistics and traffic congestion, of the thesis is presented to outline the research scope and objectives.

In Chapter 2, a structured literature review is conducted on the general reviews of previous EL research, the various emergency supply planning and evacuation planning models, as well as the approaches of applying VDFs to model traffic congestion delays. The review identifies three research gaps, which are filled in the thesis.

In Chapter 3, a stochastic MINLP model is proposed to address the two-stage traffic

congestion delays incorporated emergency supply planning problem. With the application of the BPR function to estimate the expected post-disaster transportation cost, the proposed model generalizes the previous model to produce the real optimal plan for the disaster-prone areas, where serious post-disaster traffic congestion delays are expected. We apply the GBD algorithm to solve the proposed model for relatively large instances. Moreover, a real-world case study is conducted to show the benefits of the proposed model and to generate the following managerial insights:

- When traffic congestion delays are incorporated, a better plan can be achieved through decentralizing supply storage and reducing total pre-positioned amounts of certain supplies, as well as through choosing less congested arcs and utilizing multiple routes for transportation for an origin-destination pair;
- It is recommended to let the budget limit for controlling traffic congestion delays be equal to or be slightly higher than the optimal value gap between Model (P) and Model (CP);
- Setting up policies that ensure enough capacities for the key arcs after disasters can be most effective to reduce expected traffic congestion delays. Particularly, the policy of restricting non-emergency heavy vehicles from entering the key areas is highly recommended;
- Although Model (P) is more robust to the BPR function coefficients, it is still necessary to obtain the specific BPR coefficients of each road in real-world applications.

Furthermore, the case study verifies that our GBD-based algorithm outperforms direct solving with popular MINLP solvers.

In Chapter 4, a time-space network based MIP model is developed to solve the DFEWS-based dynamic evacuation planning problem in debris flow prone areas. To our best knowledge, this is the first evacuation planning model that explicitly aims to facilitate an evacuation system in field practice. Our model not only integrates three evacuation strategies (mobilization, staging, and routing) to accelerate evacuation, but also incorporates human behavior, the S-curve demand loading pattern, and traffic congestion delays to enhance practicability of the resulting plans. The proposed model is

able to complement a real-world DFEWS, and its effectiveness is verified with an illustrative case study, which also helps to generate the following conclusions:

- Guiding the early voluntary evacuees to farther shelters, though seems unfair, benefits the entire system through achieving an early evacuation clearance time;
- Explicitly considering traffic congestion delays in the dynamic evacuation planning process not only avoids over- or under-utilization of limited transportation capacities, but also enables the resulting plans to be more practical for areas where traffic congestion delays are expected;
- It is shown that the staging strategy is another effective approach, besides evacuation routing, to reduce traffic congestion delays;
- Three policies (increasing the capacities of key arcs, increasing the maximum holding periods after the red alarm, and encouraging more active voluntary evacuation) are suggested with different priorities to turn a dangerous evacuation plan into a safe one.

Finally, the solving challenge and the application benefits of our Model (**P-L**) are discussed.

In short, the thesis highlights the importance of considering the traffic congestion factor in formulating more practical and realistic EL planning models. Although incorporating traffic congestion brings about challenges in model formulation and solvability, its benefits of producing better managerial insights and enhancing EL performances definitely worth the challenges.

5.2 Major Contributions of the Thesis

The thesis mainly contributes in the following five aspects:

- 1). Conduct a detailed literature review on various emergency supply and evacuation planning models and on traffic congestion under emergency situations to reveal research gaps;
- 2). Develop a novel two-stage stochastic supply planning MINLP model and an associated GBD-based algorithm to fill the research gap that no emergency supply planning

model explicitly considers traffic congestion delays with VDFs;

3). Propose a novel MIP model, based on a generalized time-space network, to deal with the DFEWS-based dynamic evacuation planning problem in debris flow prone areas where traffic congestion delays are expected during evacuation;

5). Aid in generating managerial insights and policies for reducing traffic congestion delays during emergency supply delivery and evacuation;

6). Help to enhance EL performances and to fulfill basic humanitarian goals of EL better.

5.3 Future Work

Our future work will continue to focus on developing novel EL planning models through incorporating more realistic factors and relationships into the planning process as well as through adopting more appropriate assumptions. In general, our future work can be conducted on emergency supply planning, evacuation planning, and integrated planning for supply and evacuation.

5.3.1 Emergency Supply Planning

The research for emergency supply planning can be extended in the following four directions.

First, if supplies have already been pre-positioned in the past, planners can decrease expected traffic congestion delays by upgrading the transportation network, such as building new roads, expanding the capacities of existing roads, and reallocating the road capacities of different directions, before disasters. Due to the limited resources and budget in the preparedness stage, the network design should be properly planned, and the planning problem deserves more investigations.

Second, we can incorporate traffic congestion delays in a two-stage multi-period transportation planning framework, such as the research of Alem *et al.* [2], to reflect the time-varying transportation conditions and demands after disasters. Although this research direction contributes to bringing about a more realistic, detailed and time-

varying post-disaster transportation plan, it leads to a complicated problem structure, which presents more challenges in both modeling and algorithm development.

Third, besides traffic congestion delays, factors like material convergence, human behaviors and psychology impacts, can be incorporated in future emergency supply planning models. Specifically, victims may show panic and selfishness behavior under emergency situation, and driver psychological and behavioral uncertainties may exist when driving on the damaged arcs. However, to properly represent such factors in our future work, we have to know more about their background and impacts based on findings of social science, as well as their relationships with emergency supply planning decisions in the first place.

Forth, we can apply game theory in formulating novel congestion delays incorporated supply planning models. For example, Bell *et al.* [12] present a game theoretic approach for modeling degradable transportation networks. In their model, the mixed strategy Nash equilibrium for the non-cooperative zero-sum game between dispatchers and demons is used to define rescue hyperpaths, which are further used to decide depot locations. Similarly, we may assume that a demon has the power to cause traffic congestion delays after disasters and incorporating the game theoretical approach into a two-stage supply planning framework to facilitate practices of the supply pre-positioning strategy.

5.3.2 Evacuation Planning

In the future, our evacuation planning research will focus on producing an efficient heuristic algorithm for the proposed Model (**P-L**) and on developing other evacuation planning models.

Model (**P-L**) is hard to solve due to its application of the generalized time-space network. The structure of Model (**P-L**) is not proper for applying large-scale decomposition-based exact algorithms. Thus, it is necessary to develop an efficient meta-heuristic or problem-specific heuristic algorithm for Model (**P-L**) to deal with relatively large instances. Moreover, it is equally necessary to conduct a real-world case study to verify the proposed algorithm and to highlight the field application value of Model (**P-L**). The

real-world case study will be based on a debris-flow-prone area in Taiwan, and we must conduct detailed disaster analyses, social investigations and scenario designs to set up the parameters reasonably.

Model (**P-L**) can also be improved with more appropriate modeling assumptions. For example, currently, Model (**P-L**) is based on the assumption that the red alarm must be given at a time after the yellow alarm. However, in field practice, it is possible that only the yellow alarm is issued. While adopting more general assumptions tends to complicate the model formulation, it is worthy as long as the resulting model is more practical and realistic.

Incorporating human behavior factors in the evacuation planning process is another critical future research direction. Since evacuation planning serves to protect evacuees, the behavior of evacuees is vital to a successful plan. However, this is challenging as many behavior-relevant social findings cannot be directly converted into mathematical formulations. To deal with the challenge, Trainor *et al.* [105] review the evacuation modeling approaches from social science and transportation engineering, and suggest an interdisciplinary five-step evacuation modeling process for future research. Hu *et al.* [56] propose a model to address the post-disaster evacuation and temporary resettlement problem considering the psychological penalty due to panic and panic spread over time. Although our Model (**P-L**) considers the demand loading behavior with S-curve, this is far from enough, and more human behavior incorporated research are required in the future.

5.3.3 Integrated Planning for Emergency Supply and Evacuation

Since supply and evacuation are closely related to each other in reality, proposing a model that facilitates the integrated planning of supply and evacuation is meaningful to avoid issues, like a supply-demand mismatch, at shelters.

While supplies are delivered from outside warehouses to disaster sites, evacuees flow in the opposite direction, that is, from disaster sites to outside shelters. For simplicity, evacuees can be viewed as a special supply with unique features and extra requirements. However, to materialize integrated planning, the factors and relationships, which influ-

ence supply and evacuation planning decisions, should be clearly identified and defined based on field practices. For example, the factor, composition of victims in a household, may be considered since it tends to influence the emergency relief and evacuation decisions and performance. Recently, Üster and Dalal [111] present an integrated planning model to establish an emergency network, which includes evacuation sources, shelters, and distribution centers. Their MIP model makes decisions of (i) center locations, (ii) shelter locations and capacity levels, and (iii) source-to-shelter and center-to-shelter assignments and corresponding flows under two goals, that is, minimizing the maximum evacuation source-to-shelter evacuee travel distance and minimizing the total cost incurred by the system. However, their model ignores routing of evacuees and supplies, uncertainty, and en route interactions between evacuee and supply flows. We believe that field investigation and interdisciplinary cooperation are indispensable to develop a practical model that aids in the integrated planning of supply and evacuation in the future.

All in all, as the trend that EL becomes increasingly crucial in reducing disaster impacts will continue in the future, the future work of developing more realistic EL models is significant, which not only leads to the advancement of EL research community but also contributes to humankind's progress of civilization and happiness.

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Appendix A. Case Study Parameters

Table A1: Supply demands of each sample hurricane

Hurricane	demand node	Water demand rate	Food demand rate	MK demand rate
1. Alicia	5	11.5	10	0.15
	4	2.5	2	0.1
	3	4.5	4	0.1
	2	1	1	0.05
	1	0.5	0.5	0.05
	10	0.5	0.5	0.05
2. Camille	14	1	0.5	0.1
	13	17	16.5	0.2
	15	2.5	2.5	0.05
	8	0.5	0	0
	7	3	3	0.05
	17	2.5	2.5	0.05
	16	6.5	6.5	0.05
3. Bonnie	21	4	1	0.1
	22	18	2.5	0.15
	20	18	2	0.15
	19	10.5	1	0.1
4. Floyd	21	29	3	0.25
	22	152.5	16.5	0.5
	20	150	16.5	0.5
	19	175	19	0.5
	23	20	2.5	0.25
5. Andrew	29	225	30.5	0.5
	28	116.5	16	0.25
	30	1	0	0
	27	47.5	6.5	0.1
	13	39	5.5	0.1
	11	6.5	1	0.05
	10	2	0.5	0
	14	0.5	0	0

	8	0.5	0	0
	9	0.5	0	0
6. Opal	15	7	7.5	0.1
	14	1.5	1.5	0.05
	24	6.5	6.5	0.1
	16	12	13	0.25
	13	31.5	33.5	0.5
7. Isabel	21	3	1	0
	22	7.5	2.5	0.1
	20	16	5	0.15
	19	9	2.5	0.25
8. Lili	10	3	0.5	0.05
	11	10.5	0.5	0.05
	13	59	3.5	0.2
	9	2	0	0
	6	3	0.5	0.1
	7	10.5	0.5	0.1
9. Katrina	29	16.5	127	12.5
	28	8.5	66	6.5
	30	0.5	1	0.25
	27	5.5	40.5	4
	13	22	165	16.5
	11	3	23	2.5
	10	1	5	0.5
	14	0.5	0.5	0.25
	8	0.5	0.25	0
	9	0.5	0.25	0
	15	2.5	20	2
10. Bertha	21	6.5	1.5	1
	22	52	15	3.5
	20	34	10	2
	19	39.5	11.5	2.5
11. Fran	21	16	3	0.5
	22	85	17	1.5
	20	83.5	17.5	1.5
	19	97	19.5	2
	23	11	2	0.5
12. Dennis	15	548.5	11	1
	24	485	10	0.5
	14	5	0.2	0.5
	8	3	0.05	0.25
	30	11.5	0.25	0.25

13. Emily	21	165	3	0.5
14. Georges	29	88.5	33.5	3
	30	1	0.5	0.25
	13	34.5	13	1
	14	0.5	0.5	0.25
	15	6.5	2.5	0.5
15. Hugo	22	101.5	52	5.5
	21	6.5	3.5	0.5
	19	86.5	44.5	4.5
	20	50	25.5	2.5
	23	13	7	0.5

Table A2: Free flow transportatton time of each bidirectional arc

Arc	Time (hours)	Arc	Time (hours)	Arc	Time (hours)
(1,2)	2.4	(1,3)	4	(2,3)	2
(2,5)	3.1	(3,4)	3.9	(3,5)	2.8
(4,6)	4.5	(4,9)	2.6	(4,10)	4.4
(4,5)	3.3	(5,10)	1.3	(6,7)	2.1
(6,9)	3.2	(7,8)	2.9	(7,16)	3.4
(7,17)	3	(8,9)	3.2	(8,12)	1.9
(8,14)	2.6	(8,16)	3.4	(9,10)	3.5
(9,11)	3	(10,11)	2	(11,12)	1.6
(11,13)	2.1	(12,13)	1	(12,14)	1.6
(14,15)	1	(15,16)	3.5	(15,18)	4.4
(15,24)	3.4	(16,17)	2.7	(16,18)	2.1
(17,18)	3.6	(17,20)	6.2	(18,19)	3
(18,20)	3.5	(18,23)	3.6	(18,24)	4.3
(18,25)	4.1	(19,20)	1.4	(19,21)	3
(19,22)	1.8	(20,21)	3.4	(21,22)	3.1
(22,23)	1.9	(23,26)	2	(24,25)	1.6
(25,26)	1	(25,27)	2.3	(25,28)	2.5
(26,27)	2	(27,28)	1.3	(27,29)	3.3
(28,29)	3.9	(29,30)	3.1		

Table A3: Arc parameters of the spatial network

Arcs (p, q)	Practical capacity c_{pq}	Free flow time t_{pq}^0	En route penalty ρ_{pq}
(o,1)	-	0	6
(o,2)	-	0	6
(o,3)	-	0	6
(7,e)	-	0	0
(8,e)	-	0	0
(9,e)	-	0	0
(10,e)	-	0	0
(1,1)	-	1	6
(2,2)	-	1	6
(3,3)	-	1	6
(1,4)	type 1	0.5	3
(2,4)	type 1	1.2	3
(2,5)	type 1	1.5	3
(3,5)	type 1	0.8	3
(4,6)	type 3	3.8	2
(5,6)	type 3	4.3	2
(6,7)	type 2	1.2	1
(6,8)	type 2	0.6	1
(6,9)	type 2	1.2	1
(6,10)	type 2	2.5	1