ABSTRACT

Title of Document: OPTIMIZATION MODELS AND METHODOLOGIES TO SUPPORT EMERGENCY PREPAREDNESS AND POST-DISASTER RESPONSE

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This dissertation addresses three important optimization problems arising during the phases of pre-disaster emergency preparedness and post-disaster response in time-dependent, stochastic and dynamic environments.

The first problem studied is the building evacuation problem with shared information (BEPSI), which seeks a set of evacuation routes and the assignment of evacuees to these routes with the minimum total evacuation time. The BEPSI incorporates the constraints of shared information in providing on-line instructions to evacuees and ensures that evacuees departing from an intermediate or source location at a mutual point in time receive common instructions. A mixed-integer linear program is formulated for the BEPSI and an exact technique based on Benders decomposition is proposed for its solution. Numerical experiments conducted on a mid-sized real-world example demonstrate the effectiveness of the proposed algorithm.

The second problem addressed is the network resilience problem (NRP), involving

an indicator of network resilience proposed to quantify the ability of a network to recover from randomly arising disruptions resulting from a disaster event. A stochastic, mixed integer program is proposed for quantifying network resilience and identifying the optimal post-event course of action to take. A solution technique based on concepts of Benders decomposition, column generation and Monte Carlo simulation is proposed. Experiments were conducted to illustrate the resilience concept and procedure for its measurement, and to assess the role of network topology in its magnitude.

The last problem addressed is the urban search and rescue team deployment problem (USAR-TDP). The USAR-TDP seeks an optimal deployment of USAR teams to disaster sites, including the order of site visits, with the ultimate goal of maximizing the expected number of saved lives over the search and rescue period. A multistage stochastic program is proposed to capture problem uncertainty and dynamics. The solution technique involves the solution of a sequence of interrelated two-stage stochastic programs with recourse. A column generation-based technique is proposed for the solution of each problem instance arising as the start of each decision epoch over a time horizon. Numerical experiments conducted on an example of the 2010 Haiti earthquake are presented to illustrate the effectiveness of the proposed approach.

OPTIMIZATION MODELS AND METHODOLOGIES TO SUPPORT EMERGENCY PREPAREDNESS AND POST-DISASTER RESPONSE

By

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Chapter 1 Introduction

1.1 Motivation and objectives

Large-scale (area-wide) disasters, e.g. natural (e.g. hurricane, tornado, earthquake, flooding, or fire) or human-induced (riot, accidental or terrorist), impose extensive physical, social and economic losses, and cause large death tolls and injuries every year. Such extreme events have exposed the vulnerability of lifeline systems and the need to mitigate the consequent risk to disruption of these systems. The transportation system, the focus of this effort, is of utmost importance in the event of a physical disaster. The functionality and performance of this system in a disaster-impacted area can directly affect the level of success in coping with the disaster. Evacuation of survivors to safer locations, on-site provision of medical assistance and movement of injured people to medical facilities, access by emergency personnel and delivery of supplies to a disaster zone are just a few examples that illustrate the importance of the transportation system in the aftermath of a disaster. Recovery and restoration of any lifeline system will very much depend on the ability of the transportation system to provide effective transport services (Nicholson and Du, 1997). For example, following the May 12, 2008 earthquake in Sichuan, China, widespread disruptions to the transportation system caused by the actual seismic event, its aftershocks and resulting mudslides greatly obstructed emergency response activities, resulting in unnecessary lost lives. Additionally, an operating transportation system is crucial to disaster recovery and continued substandard operating levels can have long-term economic impact (Chang, 2000).

Recent recognition that the transportation system not only supports the daily movement of people and goods from one place to another, but also provides accessibility to a disaster region and the ability to escape from the region, and supports recovery after the disaster, has lead to increased attention by researchers to the role of transportation in disaster preparedness and response. A number of publications have appeared in the literature that, with specific concern for the role of transportation, document experience gained from previous disaster events (e.g. Schiff, 1995; Giuliano and Golob, 1998; Willson, 1998; Chang and Nojima, 2001; U.S.DOT, 2002; Nyman et al., 2003) and propose methodologies for creating strategies to improve coping mechanisms for future events (e.g. Cho et al., 2001; Bryson et al., 2002; Okasaki, 2003; Johnston, 2004; Ham et al., 2005). These latter works consider evacuation and emergency response aimed at mitigating the impact of the event on society.

Optimal decision-making in preparing for and mitigating the impact of disaster is impeded by the complexity and intractability of the underlying problems. This is, in part, because the transportation system involves multiple transport modes with complex systems of interdependent passageways, large geographic regions, large demand for assistance or resources, uncertain intensity of disruptions, and uncertain consequences. Although some problems are tactical (e.g. pre-disaster evacuation planning), other problems are operational, requiring solution in real time (e.g. dispatching search and rescue teams post-disaster). Thus, optimization-based methods may be beneficial.

Optimization techniques are particularly useful to decision-makers when quick decisions must be taken given large quantities of input data. Such methods have been successfully applied in schedule recovery in the aftermath of disruptions in both air and rail industries (e.g. Clarke, 1997; Lettovsky et al., 2000; Thengvall et al., 2001 & 2003; Rosenberger et al., 2003). Given that future disasters are expected to increase in frequency and consequence (as noted in numerous writings, e.g. Turner and Pidgeon, 1997), additional research is required in creating disaster-resilient transportation systems and in mitigating ensuing damage. This dissertation proposes optimization-based methodologies in terms of problem formulation and solution techniques for pre-event disaster planning, post-event response and recovery, and building disaster-resistant transportation systems.

Driven by the needs and research challenges described above, this dissertation research has the following objectives:

Address vital aspects in optimization of transportation systems in pre- and post- disaster situations. Due to the intrinsic uncertain nature of disasters in terms of both their causes and consequences, damage to the transportation system and required response actions are difficult to forecast in advance. This research seeks to provide fundamental insight into aspects of the following comprehensive questions: (1) How resilient is the transportation network to disaster? (2) How best to evacuate people to safety? (3) How to optimally deploy emergency personnel and allocate supplies in a large-scale disaster involving multiple disaster sites.

Develop models for these identified optimization problems. Mathematical models of the optimization problems addressed within this dissertation are formulated and their inherent uncertain and time-dependent characteristics are considered. The output of the models is (1) the measurement of the transportation system's recovery capability and optimal selection of recovery activities, (2) pre-disaster evacuation plans, and (3) post-disaster emergency workforce and equipment deployment actions.

Provide conceptual frameworks and specific methodological procedures for solution of identified optimization problems. A variety of algorithmic approaches, including, for example, Benders decomposition and other exact or approximation integer programming techniques, are developed for solving these problems. No prior work in the literature has addressed these problems with the inherent complexities considered herein. The developed methodologies were employed on real-world and carefully created fictitious networks to examine and demonstrate their effectiveness.

1.2 Specific problems addressed

This dissertation work has arisen from the increasing concerns, both nationally and internationally, for securing existing transportation systems. This work seeks to address important aspects of pre-disaster emergency preparedness and post-disaster response and recovery. While it is widely recognized that transportation systems are critical to preserving mobility and general functionality of society and its economy, systematic and quantitative research in this arena has been limited. This section provides a concise statement of each of the problems addressed within this dissertation, the analytical approach employed for their solution, and their import to reducing the negative consequences of a disaster. Formal definitions, together with detailed description of the problem formulations and solution approaches, are given in Chapters 3 through 5.

1.2.1 The Building Evacuation Problem with Shared Information (BEPSI)

The BEPSI is addressed in this dissertation. Its objective is to determine a set of evacuation routes and the assignment of evacuees to these routes for a large burning building or a building that has come under attack by enemy or natural catastrophe such that the total evacuation time is minimized. Resulting routes can be updated in response to new information ascertained about the operational capacity of the building's circulation systems (i.e. the means of egress) and updated evacuation instructions can be provided in real-time to the evacuees. Given existing technologies that can be employed for this purpose, instructions that are provided at a particular location in the building will likely be simultaneously received by many evacuees. If multiple options are provided, confusion and/or chaos could ensue. Existing optimization approaches in the literature cannot guarantee that common instructions will be generated at intermediate locations at any given point in time.

In this dissertation, the BEPSI is formulated as a mixed-integer linear program, where the objective is to determine the set of routes along which to send evacuees (supply) from multiple locations throughout a building (sources) to the exits (sinks) such that the total time until all evacuees reach the exits is minimized. The formulation explicitly incorporates the constraints of shared information in providing on-line instructions to evacuees, ensuring that evacuees departing from an intermediate or source location at a mutual point in time receive common instructions. Arc travel time and capacity, as well as supply at the nodes, are permitted to vary with time and capacity is assumed to be recaptured over time. The BEPSI is shown to be NP-hard. An exact technique based on Benders decomposition is proposed for its solution. This work is expected to impact other functional areas as well, including evacuation of a geographic region due to military attack, human-made accident, or natural disaster. Details of the formulation, together with the proposed algorithmic approach and results of its application on a real-world example representing a four-story building, are given in Chapter 3.

1.2.2 The Network Resilience Problem (NPR)

Individuals and companies have become increasingly dependent on the freight transport system to deliver their goods, and thus, significant increase in demand for freight transport in coming years is anticipated. However, the freight transport sector is operating at or near its capacity in many regions of the world, including the United States, and yet an increase in the capacity of such systems is not anticipated. Simultaneously, risks from accidents, weather-induced hazards, and terrorist attack on freight transport systems have dramatically increased. Thus, trucking companies, rail carriers, infrastructure managers, and terminal and port operators must invest in security measures to prevent or mitigate the effects of disasters resulting from such incidents. Thus, there is increased pressure on the freight transport industry to balance conflicting objectives of providing high service and security levels while simultaneously offering low cost transport alternatives.

An indicator of network resilience is proposed that quantifies the ability of an intermodal freight transport network to recover from random disruptions due to natural or human-caused disaster. The indicator explicitly considers recovery activities that might be taken in the immediate aftermath of a disruption, as well as the duration of time, investment and other resources required to undertake related actions.

A stochastic integer program is proposed for quantifying network resilience and identifying the optimal course of action (i.e. set of activities) to take in the immediate aftermath of a disaster given target operational levels and a fixed budget. To solve this mathematical program, a technique that accounts for dependencies in random link capacities based on concepts of Benders decomposition, column generation and Monte Carlo simulation is proposed. The technique is illustrated on the Double-Stack Container Network. Formulation of the Network Resilience Problem and the technique proposed for its solution are presented in Chapter 4.

1.2.3 The Urban Search and Rescue Team Deployment Problem (USAR-TDP)

The problem of determining the optimal deployment of USAR teams to disaster sites within the disaster region, including the order of site visits, with the ultimate goal of maximizing the expected number of saved lives over the search and rescue period, referred to herein as the USAR team deployment problem (USAR-TDP), is addressed in Chapter 5. The problem is motivated by the need to quickly respond to a disaster to mitigate negative impacts. In an urban area that has been struck by disaster, where the impact area contains numerous sites, such as where buildings or other structures suspected of housing people stood prior to the disaster, it is crucial that urban search and rescue (USAR) teams be quickly deployed. In such situations, there is a need for quick decision-making despite the inherent unstable and uncertain nature of circumstances immediately following disasters of this type.

USAR-TDP seeks to identify a set of non-overlapping tours for USAR teams so as to maximize the total expected number of people that can be saved by attending to all or a subset of disaster sites within the disaster region. To address the probabilistic and dynamic nature of conditions following a disaster, the on-site service times are assumed to be uncertain and sites requiring assistance are identified dynamically over the decision horizon. A multistage stochastic, integer program is formulated to model the sequential stochastic information process.

To overcome the expensive computational effort associated with the solution of a multistage stochastic program, a column generation-based methodology is developed to solve a sequence of interrelated two-stage stochastic programs with recourse within a shrinking-horizon framework. Interactions among teams are considered and set partitioning-type formulations are developed in terms of different recourse actions. Such solution will aid the incident commander in determining the best deployment strategy for available USAR task forces by directing crucial assets to sites within the impact area, where the most good can be done in the first days of the emergency period. To illustrate the feasibility and efficiency of applying the proposed solution technique in support of USAR operations in real-world applications, experimental results from a test case are developed to replicate events of the 2010 Haiti earthquake.

1.3 Contributions

Three important problems associated with evacuation, network vulnerability and emergency response operations, none of which was previously conceived in the literature, are conceptualized and mathematically formulated. Such formulations provide precise problem definitions and permit quantitative analyses of real-world problem instances. The inherent probabilistic and dynamic nature of real-world conditions following a disaster is explicitly addressed. Exact or approximation solution methodologies are proposed to address these problems. Such solution techniques provide support to decision-makers faced with difficult, urgent decisions arising in emergency preparedness planning and post-disaster response. The problems addressed in this dissertation research are either shown to be NP-hard or their deterministic versions are NP-hard, and thus, are known to be difficult problems. Computational experiments are conducted to test the effectiveness and efficiency of the proposed solution procedures.

In addition to the mathematical and methodological contributions associated with strategies for evacuation, response and recovery, an exposition of security concerns associated with transportation systems, including the role of transportation in emergency management and in supporting other critical lifelines, as well as the transportation network as the target of natural or terrorist attack, is provided. This focused discussion provides a viewpoint for considering how the issues tackled within this dissertation fit within the larger concerns of security and the movement of people and critical resources and supplies.

Natural and accidental events, as well as terrorist attacks, can impose extensive damage to society. Such events are increasing in frequency (e.g. FEMA, 2008) and the likelihood that the impact of such adverse events will be disastrous has been rising (e.g. Bureau for Crisis Prevention and Recovery, 2004). Thus, it is critical that governments, related non-governmental organizations (NGOs) and local citizen groups be prepared for large-scale disasters. Lack of appropriate preparedness and response actions could lead to needless injuries, lost lives and property loss. This dissertation research takes into account society's need for safety in the case of disaster or terrorism resulting in region-wide destruction and will support emergency preparedness and response by providing tools to aid in pre- and post-disaster decision-making.

1.4 Dissertation organization

The remainder of this dissertation proposal is organized in five chapters. Chapter 2 presents a discussion of the role of the transportation system in emergency preparedness and response and includes insights into emergency preparedness and response pertaining to events that impact the transportation system itself. Chapters 3 through 5 address the BEPSI, NRP and USAR-TDP discussed in this chapter. Finally, in Chapter 6, conclusions and extensions for future research are given.

Chapter 2 Disaster and the Transportation System

This chapter presents general background literature for this dissertation and is divided into three sections. In the first section, a general overview of previous studies pertaining to disasters and the transportation system's unique role in disaster is presented. The next two sections are devoted to emergency preparedness and disaster response associated with disaster events affecting the transportation system.

2.1 Transportation Systems in Disaster

Disasters are the result of interactions between the earth's physical systems, human systems and the constructed environment (Mileti, 1999a). Turner and Pidgeon (1997), among others, posit that many of the hazards that society faces today are the result of human intervention in environmental processes (e.g. through depletion of the ozone layer, deforestation, and genetic modification of organisms), manufacturing of hazardous substances, and the creation of engineered systems with the potential for accidental catastrophic destruction. The development of such engineered systems and associated technologies, e.g. nuclear power, biological chemistry and computers, as well as increased globalization, have amplified human vulnerability to disaster. The Center for Research on the Epidemiology of Disasters (CRED) reported that there were more than

16,000 mass disasters that impacted human society from 1900 to the present. Under a different definition of disaster, Alexander (2005) estimates that in recent years, the annual rate of natural catastrophe and technological disaster has been on the order of 220 and 70, respectively, around the world.

Disasters, by definition, impose extensive damage to society and the likelihood that the impact of an adverse event will be disastrous continues to rise. This increasing destructive power of disaster events is due in large part to increases in world population and dense concentration of that population in vulnerable areas, such as along the coast, raising the likelihood that any major hazardous event will adversely affect societies with large numbers of people and significantly advanced civil infrastructure (see Turner and Pidgeon (1997) for additional insights). As evidence of this increase, in the U.S., the average number of declared disasters has risen from 10 per year in the 1950's to over 40 per year at the beginning of this century (Figure 2-1, FEMA, 2008). Additionally, the economic impact of these events continues to rise in absolute terms (see Figure 2-2) without considering the indirect costs caused by business disruptions (Bureau for Crisis Prevention and Recovery, 2004). The Munich Re Group estimates that annual worldwide losses due to disaster in the 1990s were eight times greater than in the 1960s (United Nations Development Programme, 2004).

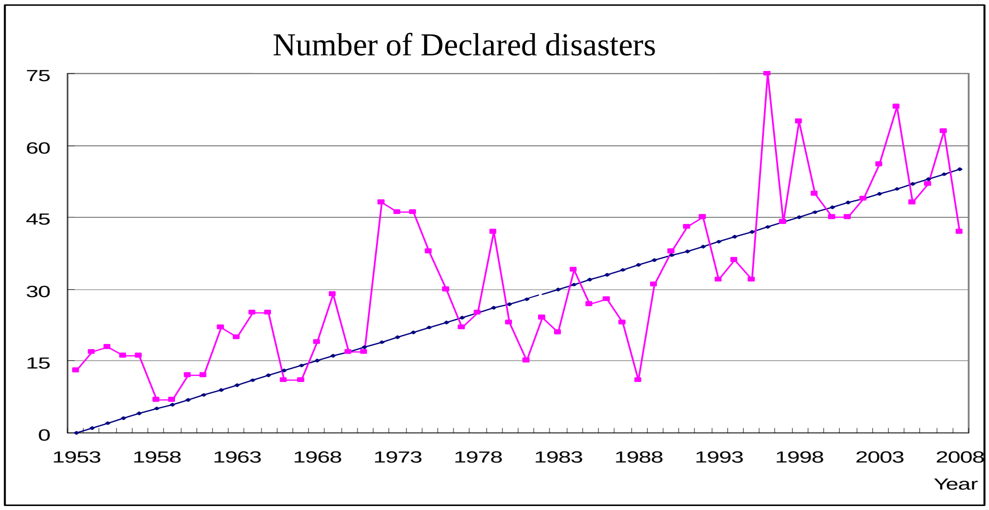


Figure 2-1 Annual number of declared disasters

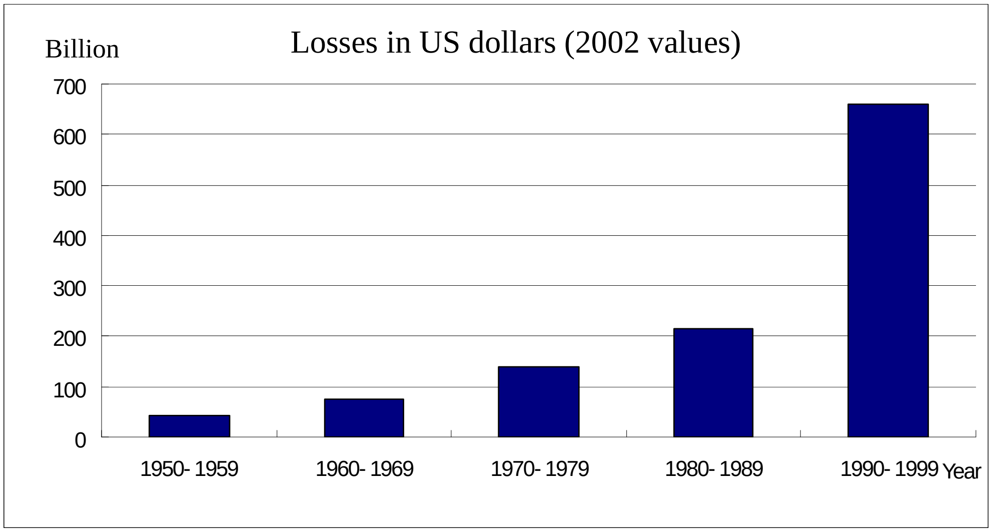


Figure 2-2 Global economic losses due to natural disasters (in 2002 values)

Source: The Munich Re Group

Recent events, including the Southeast Asian Tsunami (2004), Hurricane Katrina (2005), Pakistani earthquake (2005), Myanmar cyclone (2008) and the earthquake in China (2008), have made the first decade of this century the costliest on record. Disasters present an extraordinarily complicated and incredibly challenging problem for human societies in planning for and managing such negative occurrences. Better understanding of disasters and improved preparedness and response capabilities has the potential to save an enormous number of lives and to significantly reduce economic losses.

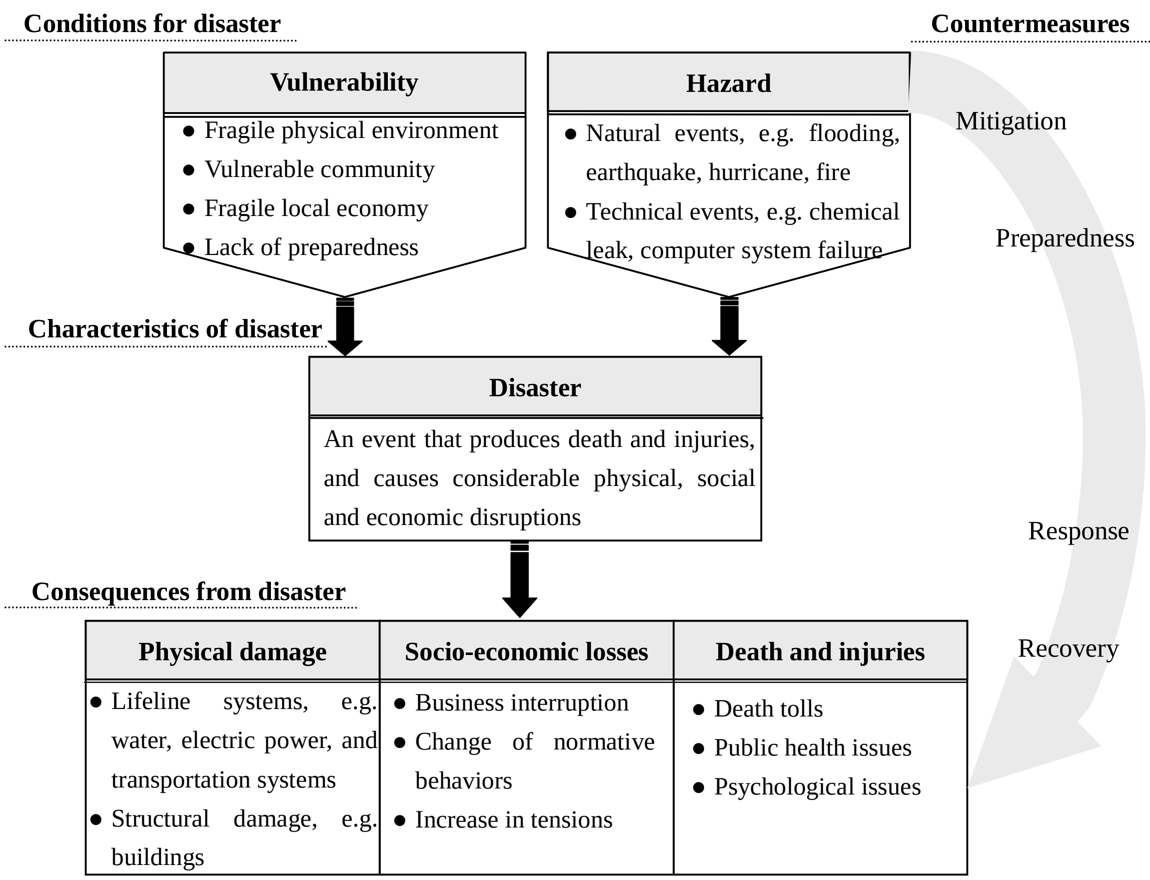


Figure 2-3 Dimensions of Disaster Research

Disaster research began in the 1950s (Perry, 2007). This research has covered such topics as case studies, human behavior and governmental activity in disasters, modeling of infrastructure development, and systematization of disaster management services. Alexander (1997) has claimed that some 30 disciplines, including sociology, geography, anthropology, politics and engineering, have an interest in the disasters field. Only recently, but rarely, have quantitative studies been conducted. Figure 2-3 provides a conceptual framework of disaster research, which shows the dimensions characterizing a disaster and describes the disaster countermeasures.

In past decades, the development of new technologies, e.g. nuclear power, biological chemistry and computers, as well as social and economic transformations, e.g. increasing population density and aggregation, international trade competition and globalization, and industrial change in production and distribution of goods and services, have increased human vulnerability to disaster. Moreover, recent escalation in terrorist attacks and the potential lethality of weapons obtained by terrorist organizations have created new threats. Thus, in recent years, our civilizations have become increasingly susceptible to nontraditional disaster events as compared to the past (Quarantelli et al., 2007). New efforts to understand and cope with disasters are crucial.

The transportation system plays a critical role in coping with disasters. This system is composed of numerous modes (highway, rail, air, marine, and pipeline), is a vast, open, interdependent networked system that moves vast numbers of passengers and quantities of goods nationally and globally. While the transportation system is critical to coping with disasters, the transportation system may be seriously impacted during a disaster. For example, the 1994 earthquake on the Hayward Fault in the San Francisco area resulted in more than 1,600 road closures and damage to most toll bridges and major highways (Okasaki, 2003). However, systematic study of the role of the transportation system in disasters has only recently begun to be considered. The study of disasters and physical structures and concerns of behavioral and social sciences are far more mature fields of study. The majority of relevant transportation related research has focused on such topics as performance analysis, disaster impact evaluation, and evacuation.

The transportation system is a critical lifeline system that affects any nation's way of life, economic vitality and society, in general. In the U.S., the transportation system connects cities, manufacturers, and retailers, moving large volumes of goods and people through a network of 3.8 million miles of roadways, more than 143,000 miles of rail, over 582,000 bridges, through numerous sea ports, and over 500 public airports (U.S. Department of Homeland Security, 2007). Destruction of and damage to transportation systems results in, not only direct disruptions of transportation services, but also in indirect economic losses and sociological effects. After the attack of September 11, 2001, one of the largest terrorist-caused disasters, more than $5.5 billion was required to rebuild the transportation system in lower Manhattan (Waugh, 2007).

In the aftermath of a disaster, transportation systems provide essential access for emergency personnel carrying critical resources to disaster sites and allow for the evacuation of people and property from those sites. On September 11, 2001, public transportation in New York City, New Jersey, Washington, D.C. and throughout the country helped to safely evacuate citizens from city centers. Around 750,000 people were evacuated by water transportation from lower Manhattan (Kendra and Wachtendorf, 2003).

Transportation systems are essential for individuals, households, and communities as they attempt to recover from disasters. Recovery and restoration of any lifeline system will depend on the ability of the transportation system to provide effective transport services (Nicholson and Du, 1997). Chang (2000) pointed out the significance of an operating transportation system in disaster recovery and the long-term economic impact of substandard operations through empirical data from the 1995 Kobe earthquake and other disasters. Giuliano and Golob (1998) examined behavioral data collected in two heavily damaged corridors following the Northridge earthquake of 1994. They found that the transportation system's redundancy and a variety of short-term changes in individual's travel choices made rapid recovery possible even from major disasters. Willson (1998) examined the impacts of the 1994 Los Angeles County earthquake on trucking firms and how they responded to the earthquake. The author pointed out that quick restoration of transportation capacity significantly impacted goods movement.

Meanwhile, the possibility of attack on transportation systems and the use of transport vehicles as tools for terrorist attack have increased. Incidents include not only the September 11, 2001 attacks on the World Trade Center and the Pentagon, but also more recent attacks on transportation targets, such as the coordinated attack on four commuter trains in Madrid in 2004, the 2005 London underground bombings, the 2006 plot uncovered in the United Kingdom targeting airlines bound for the United States, and the 2010 Moscow metro bombings. These recent attacks provide evidence that the transportation system remains an attractive target for terrorists. As suggested by Johnston (2004), perhaps our civilization should focus less on maximizing efficiency and more on increasing security and safety of the transportation systems.

Thus, the importance of transportation systems for responding to and recovering from a disaster, and the possibility of future events involving transportation systems, presents new challenges and tasks for transportation practitioners. Recently, researchers have begun to consider the ramifications of disaster impact on transportation systems. Disaster events can negatively impact the transportation system, affecting mobility and, ultimately, the economy. Disruptions in transportation services further negatively impact disaster response. A number of publications have appeared in the literature that, with specific concern for the role of transportation, document experience gained from previous disaster events and propose methodologies for creating strategies to improve coping mechanisms for future events. These latter works consider evacuation and emergency response aimed at mitigating the impact of the event on society. In the next sections, pre-event disaster planning and post-event response are discussed in greater detail.

2.2 Preparing for Disasters

To mitigate the negative consequences to society and the physical infrastructure that might be caused by a disaster, preparedness plans can be developed and protective actions can be taken *a priori*. Preparation for disaster events includes a broad range of activities, such as vulnerability assessment, implementation of risk-reducing measures, development of disaster plans, and training. A large body of research has been conducted on emergency preparedness from various perspectives (e.g. families and households, communities, engineering systems, and states and nations) to increase the ability of such social and physical units to respond when a disaster occurs. The preparedness process begins with vulnerability assessment that seeks to identify sources of risk and associated consequences that are likely to occur in the aftermath of a disaster event. Risk-reducing measures can be employed and plans for coping with disaster consequences that may not be avoided can be developed.

2.2.1 Vulnerability analysis

All societies regularly face negative events that reveal their physical and social vulnerabilities (Tierney et al., 2001). Substantially better understanding of the vulnerability of transportation systems is required to achieve a more disaster-resistant transportation system. Vulnerability of transportation systems to disasters stems from a variety of interrelated factors that include network configuration, topology, physical location, the conditions under which the system operates, and other system characteristics. Consistent with the social vulnerability paradigm, transportation system vulnerability can be thought of as stemming from not only exposure to the potential physical impacts of disasters, but also from societal conditions and trends that cause certain systems to be less able to cope with disasters. Vulnerability, thus, has both physical and social dimensions. For example, urbanization has induced greater traffic activity and placed increasing demands on the transportation infrastructure at the same time as this infrastructure is aging and in need of major investments for maintenance and/or modernization, increasing the vulnerability of transportation systems.

Sources of vulnerabilities of transportation systems are threefold: 1) concentration of populations in dense regions, high levels of vehicular traffic and high public transportation ridership; 2) inadequate capacity of transportation systems; and 3) hazardous materials transport. These sources of vulnerability are interrelated. Reduction in these vulnerabilities remains difficult, because it would place hefty costs on the transportation industry. Thus, the improvements that have been made in reducing these vulnerabilities have been small and society has chosen to remediate and mitigate damage once incurred, rather than seek to prevent it (Perrow, 2007). Srinivasan (2002) pointed out that the absence of a quantitative vulnerability analysis at both component and system-wide levels remains a serious, if not the most significant, challenge to developing insights and systematic methods to improve transportation security.

2.2.2 Risk reduction

The risk of a hazard is the product of the probability of the hazard occurring and the consequence of its occurrence (i.e. the expectation of the hazard or threat). Risk reduction is a well-established process for identifying hazards, identifying their probabilities and consequences, assessing the acceptability of the risks, and taking action to address unacceptable risks (Dalziell et al., 1999). Risk reduction is a broad concept including all aspects that will help to reduce the risks of damage, such as risk identification and assessment, risk reduction, and risk transfer. Many actions could be thought of as risk reduction. Including safety features in the design of bridges to strengthen them against collapse during future earthquakes or building alternative routes to move traffic from some origin to destination are examples of risk-reducing actions that can be taken.

Risk identification and assessment can be applied to identify the critical components of the transportation system. These methods require information about the severity of hazard and the probability of hazard occurrence. Such information is difficult to obtain and may require a substantial data collection effort and detailed knowledge of the processes underlying these hazards. Mainly, the risk to the transportation system is evaluated from direct damage to critical system components, such as bridges, and the indirect costs due to travel delays in the disrupted system (e.g. Basoz and Kiremidjian, 1996; Werner et al., 2000; Kiremidjian et al., 2007).

2.2.3 Pre-disaster planning

While it is costly to implement other risk reduction measures to sufficiently reduce vulnerability and possible consequences of disaster events, it is widely accepted that pre-disaster planning has a positive effect on the system's ability to respond effectively once a disaster occurs (Tierney et al., 2001). Pre-disaster planning provides a cost-effective way to reduce disaster risks and potential losses. Such plans pertain to evacuation, recovery, emergency response, and sheltering. Development of plans to address these various stages of emergency management aid in the system's ability to cope with adversity and are vital to the creation of a disaster-resilient system (Mileti, 1999b).

Evacuation planning is one important component of pre-disaster planning.

Optimization-based approaches are widely use to produce evacuation plans that identify routes and schedules to evacuate impacted people to safety in the event of disaster within an acceptable evacuation time (see, for example, Hamacher and Tjandra, 2001; Miller-Hooks and Stock Patterson, 2004; Lu et al., 2003; Mamada et al., 2003; Baumann and Skutella, 2006; Kamiyama et al., 2006). Recovery planning is another important component. Vocca (1992) recommends that several issues associated with redundancy be considered when developing an effective network recovery plan, i.e. that alternate routes, backup strategies, contingency plans, and people plans be included. Semer (1998) proposed six basic areas for disaster recovery planning, including impact analysis, risk assessment analysis, risk mitigation strategy development, recovery planning, alternate site consideration, and routine training. Bryson et al. (2002) proposed the use of mathematical modeling as a decision support tool for successful development of a disaster recovery plan. Dekle (2005) used a covering location model to identify optimal disaster recovery center locations, which will provide long-term recovery assistance subsequent to a declared disaster.

2.3 Responding to Disasters

Figure 2-4 shows the different phases of the disaster life cycle that take place in the aftermath of a disaster. When a disaster occurs, police, fire, emergency medical service personnel, as well as emergency managers and numerous others, are involved in the response and recovery processes within the disaster zone. These first responders partake in the provision of warning, emergency sheltering, search and rescue, ongoing situation assessment, emergency resource management, and implementation of other emergency measures. The response process has been the most studied phase of disaster (Tierney et al., 2001). The quality of the preparedness and response effort is likely to be interrelated and the effectiveness of one affects and is affected by the other. Mileti (1999b) has concluded that high levels of preparedness would enhance the system's ability to respond effectively at the time a disaster strikes.

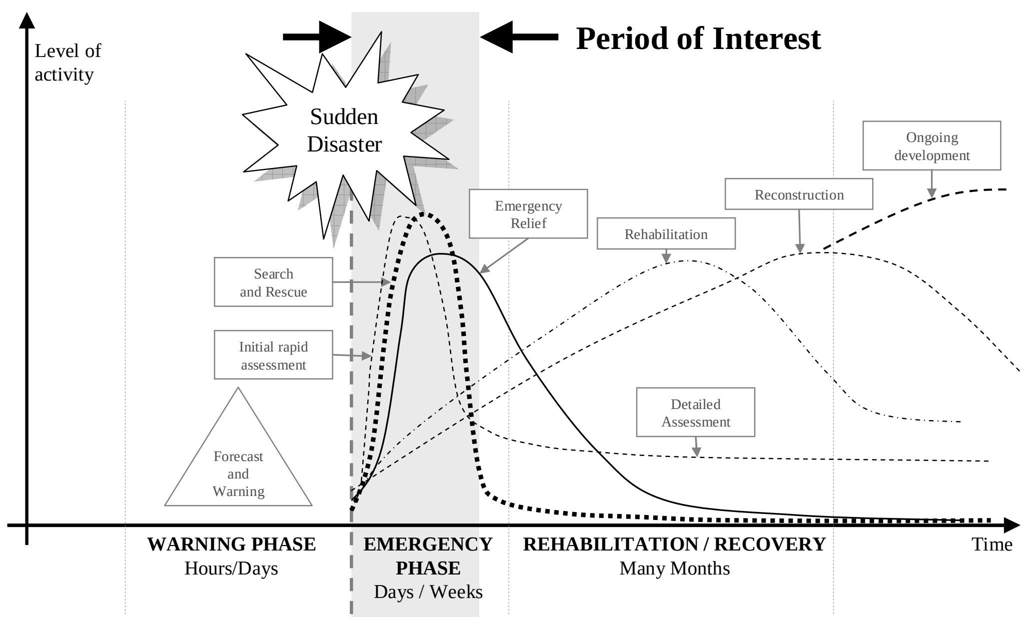


Figure 2-4 Timeline of different phases post- disaster

2.3.1 Initial response

Once a disaster has taken place, the first concern is effective relief, i.e. helping all those affected to recover from the immediate effects of the disaster. This is known as initial response and usually lasts for several weeks. Initial response includes various actions, such as assessing the conditions of transportation infrastructures, determining evacuation requirements, assisting with evacuation of people to safe places, dispatching materials, personnel, and supplies in support of emergency activities, deploying transportation agency response personnel, and adapting traffic control strategies.

Effective response to a disaster using transportation assets has the effect of minimizing the loss of life and damage to property and maintaining the basic transportation services that are needed to decrease the magnitude of negative consequences of disasters.

2.3.2 Recovery

New models of recovery have been developed since the 1970s (Mileti, 1999b). Recovery covers a variety of very complex activities that need to be addressed after a disaster, such as quick return to normalcy; reduction of future vulnerability; or opportunity for improved efficiency, equity, and amenities (see, for example, Berke et al., 1993; Batho et al., 1999; Mileti, 1999b; Hecker et al., 2000; Smith and Wenger, 2007). Recovery is not a linear phenomenon with a specific set of stages, but rather is a probabilistic and recursive process addressing decision-making associated with restoration, reconstruction, rehabilitation, and redevelopment activities. Recovery may take as long as years.

The recovery process is complex, often involving the civil infrastructure, engineered systems, the overall economy, and society, and the impact on each varies greatly with the disaster event. Thus, it may be difficult to develop a standardized recovery framework or a single model applicable to all types of disasters and impacted regions. For impacted transportation systems, recovery includes not only repairing some subset of the existing infrastructure's components, but also prioritizing and/or allocating resources necessary to maintain and restore the transportation system, and adding new components to a transportation network with the goal of creating a less vulnerable post-event network configuration. Thus, it is not only important to bring the system to normalcy in terms of providing transportation services, but it is also critical to change traveler behavior and develop a sustainable, less vulnerable and disaster resistant network for the future.

2.4 Conclusions

While extensive literature exists that addresses the subjects of preparing for and responding to disaster at various levels (e.g. households, organizations, communities, and states and nation), limited research has been conducted that is specifically related to transportation systems. While it is clearly recognized that a disaster-resistant transportation system is a critical issue in reducing injuries and death tolls, mitigating the socio-economic losses and property damage, and minimizing a myriad of disruptions, there is a dirth of works pertaining to transportation systems that mathematically model the problems arising in the preparation and response phases in support of optimal decision-making. This dissertation seeks to fill a piece of that void.

Chapter 3 The Building Evacuation Problem with Shared Information

3.1 Introduction

The Building Evacuation Problem with Shared Information (BEPSI) is addressed in this chapter. The objective of the BEPSI is to determine a set of evacuation routes and the assignment of evacuees to these routes for a large burning building or a building that has come under attack by enemy or natural catastrophe such that the total evacuation time is minimized. The term building is used generically throughout this work and refers to any structure that houses people and other assets, such as a high-rise residential building, a military complex like the Pentagon, or a large ship. Resulting routes could be updated in response to new information ascertained about the operational capacity of the building's circulation systems (i.e. the means of egress). Such routes and updates to these routes during the course of the evacuation could be provided in the form of instructions to the evacuees via changeable message signs, photoluminescent signage, voice evacuation systems, or other technologies that would support real-time public information updates in substandard conditions. Thus, any instructions that are provided at a particular location in the building will likely be simultaneously received by many evacuees. That is, evacuees departing from an intermediate or source location at a particular point in time receive common instructions as to how to proceed (i.e. shared information). If multiple options are provided, confusion could ensue. The potential for providing such updated evacuation instructions given real-time information and predictions of the condition of the building's structures and circulation systems based on data from sensor systems is described in Miller-Hooks and Krauthammer (2007). Existing optimization approaches in the literature cannot guarantee that common instructions will be generated at intermediate locations at any given point in time.

Typical building evacuation plans are developed pre-disaster for no specific threat and these plans are posted throughout the building. Such plans could, in an actual evacuation, route evacuees into harms way (e.g. to a stairwell with untenable conditions), leaving evacuees to their own devices to find alternative (safer) routes. Past experience has demonstrated that two main hindrances to the movement of evacuees in a building evacuation exist: (1) inappropriate selection of escape pathways and (2) congestion along the safest pathways (Lovas, 1998). Instructions generated for the specific circumstances leading to the need for the evacuation can lead to significant improvements in escape pathway selection. Moreover, explicit consideration of the number of people that such pathways can support in developing real-time evacuation instructions can lead to reduced congestion throughout the building and greater likelihood of successful egress.

In this chapter, the BEPSI is formulated as a mixed integer linear program, where the objective is to determine the set of routes along which to send evacuees (supply) from multiple locations throughout the building (sources) to the building exits (sinks) such that the total time required of all evacuees to reach the exits is minimized. The formulation explicitly incorporates the constraints of shared information; thus, feasible solutions must not contain more than one path from a node at a given departure time. Arc travel time and capacity, as well as supply at the nodes, are permitted to vary with time (i.e. the network is permitted to be time-varying) and capacity is assumed to be recaptured over time (i.e. the network is dynamic). Thus, the formulation can be viewed as a time-dependent, dynamic transshipment problem with side constraints. A similar distinction between time-dependence and problem dynamics is made in Miller-Hooks and Stock Patterson (2004). An exact solution technique based on Benders decomposition is proposed for solution of the BEPSI.

Optimization techniques have been proposed for use in determining optimal evacuation routes for both building and regional evacuation over the past few decades and a number of these works develop network flow-based solution techniques that consider the dynamic and, in some cases, the time-dependent network properties. See Hamacher and Tjandra (2001) and Miller-Hooks and Stock Patterson (2004) for a review of relevant works in the literature. Additional relevant works published in the past couple of years include Lu et al. (2003), Mamada et al. (2003), Baumann and Skutella (2006) and Kamiyama et al. (2006). All of these works assume that when two or more units of flow (i.e. the evacuees) arrive at an intermediate node, instructions can be provided that permit the flow to split among various routes. Thus, the instructions may, for example, send a subset of flow units along one route and the remaining units along another route. The provision of such instructions that require evacuees to separate at intermediate locations despite that they have arrived at this location together would not likely be palatable and could lead to confusion, or worse, chaos.

To corroborate this concept of a need for shared instructions, research has shown that in a crisis, such as would arise in an evacuation, people look to each other for cues in making decisions as to how to proceed (Johnson, 1974; Helbing et al., 2000). Helbing et al. (2000), for example, noted a strong tendency towards collective behavior, where people follow the actions of others in evacuations involving crowds. An emergent norm that guides the group's behavior forms as people seek coordinated, collective action (Wenger et al. 1994). In addition, Sime (1985) stated that during a fire, people will gravitate to familiar people and if groups are split, they seek to reunite during the evacuation. Wenger et al. (1998) postulated that preexisting and emergent social relationships impact collective behavior. Observations from these works support the need for providing instructions that do not require a group of evacuees arriving at an intermediate location to split apart, i.e. that support a group's desire for collective action.

A similar concept of "unsplittable flow" has been employed in formulating bin-packing, virtual-circuit routing, scheduling and load balancing problems (see, for example, Dinitz et al., 1999; Chakrabarti et al., 2002; Kolliopoulos and Stein, 2004). The unsplittable flow problem seeks to route numerous commodities each along a single route from a source to a desired sink while respecting arc capacity limitations. In the limit, if only one commodity is considered, this problem would be identical to a static version of the BEPSI with one sink and supply at only one origin. Of greater relevance, perhaps, is work by Lu et al. (2003). Their work proposed a heuristic for evacuating all evacuees who begin at a particular source node along a single route such that arc capacity limitations are respected. Multiple sources are considered. If such routes cross (i.e. are not independent), such a solution could require evacuees simultaneously arriving at an intermediate node from different origins to take different routes out of that intermediate node.

In the next section, a mathematical formulation is proposed for the BEPSI that explicitly considers the inherent dynamic and time-varying nature of the evacuation problem. By explicitly considering these characteristics, resulting solutions will avoid sending evacuees to corridors or stairwells when conditions at these locations are expected to be untenable or difficult to traverse. The author know of no works in the literature that address the issue of shared information that arises in this building evacuation problem. In addition, in the next section, the BEPSI is shown to be NP-hard. In Section 3.3, a Benders decomposition approach for solving the BEPSI is proposed and is illustrated on an example 5-node network. Computational results from numerical experiments on a real-world network representing a four-story building are given in Section 3.4. Conclusions and directions for future work are discussed in Section 3.5.

3.2 The evacuation problem with shared information

The evacuation problem with shared information exploits a network representation of a building. In such a representation, the network represents the layout of the circulation systems of the building, where nodes correspond with locations inside the building (such as offices, meeting rooms, lobbies, lavatories, building exits, and corridor intersections) and arcs correspond with the passageways that connect these locations (such as staircases, elevator shafts, doorways, corridors and ramps). A cost is often associated with the use of an arc. In evacuation problems, the cost is typically given in terms of the time it takes to traverse the arc, known as the arc traversal time. When large numbers of people must be evacuated from the building simultaneously, issues concerning capacity of the network arcs arise. The capacity of an arc is the number of people that can pass through the associated passageway per unit of time. The arc capacities are dependent upon the size and type of passageway that the arcs represent. Arc traversal times are a function of the arc capacities and the number of people simultaneously using the arcs. The nodes at which the people are located when the evacuation begins are called source nodes and the exits are referred to as sink nodes.

3.2.1 Preliminaries

Consider a time-dependent, dynamic network represented by $\Im = \left(G, u, \tau\right)$, $G = \left(N, A, \{0,...,T\}\right)$, where $N = \{1,...,n\}$ is the set of nodes, $A = \left\{(i, j) \middle| i, j \in N\right\}$ is the set of directed arcs, and T is the analysis period of interest discretized into small time intervals $\{0,...,T\}$. It is assumed that all evacuees can egress before time *T*; although, one can set a tighter bound on the evacuation time. Note that *T* may be an expert-generated bound to model physical processes, such as the time by which conditions are expected to become untenable due to smoke or fire spread or complete collapse of the building's structures. Alternatively, T may be set simply to ascertain the number of people that will escape in a given time interval. One could also seek an optimal T, i.e. the minimum time by which every evacuee could exit the building. From this latter perspective, Miller-Hooks and Stock Patterson (2004) have developed an approach for determining a bound on T that could be employed in obtaining such a bound for the problem studied herein. We focus, though, on minimizing total time, instead of minimizing T, because solutions to this latter problem can include rather poor paths for many of the evacuees. That is, there is no incentive to reduce the evacuation time of any evacuee, as long as that time is below the optimal T-bound.

Each arc $(i, j) \in A$ has associated with it a positive time-varying capacity and a nonnegative time-varying traversal time. The capacity of arc (i, j) at departure time t is denoted by $u_{ij}(t)$ with integral domain and range. Instead of representing the actual flow at any given time, the capacity of an arc is the maximum flow released on the arc at a given departure time. That is, the capacity limits the rate of flow into an arc. As flow leaves node i at some departure time t, the time it takes to reach node j, i.e. the travel time along arc (i, j), is given by positive valued $\tau_{ij}(t)$. The arc travel time is defined upon entering an arc, and is assumed to be constant for the duration of travel along that arc. Thus, it is possible for a unit of flow to leave node i ahead of some other flow, but arrive later. Travel time estimates can be obtained via historical data, sensor technologies or from a function of capacity. The methodology is general enough to support all such estimation methods.

Holdover arcs $(i,i), \forall i \in N$, are introduced at the nodes to allow evacuees to arrive at intermediate locations and wait for capacity to become available on outgoing arcs. Traversal times and capacities of the holdover arcs are set to one unit and infinity, respectively, $\forall i \in N$ at each departure time $t \in \{0,\ldots,T\}$. The traversal time of the holdover arc at the sink node is set to zero for all departure time intervals, because there is no penalty for arriving at the sink before T.

The number of source nodes is denoted by M and the set of source nodes and sink node are denoted by $K = \{k_1, k_2, ..., k_M\}$ and l, respectively. The supply at any source node k_m at time t is denoted by $b_{k_m}(t)$ and can take on positive values for any $t \in \{0,\ldots,T-1\}$. The supply of any intermediate node is assumed to be zero. Without loss of generality, it is assumed that only one sink exists. One can model additional sinks by adding a super sink to the network and connecting each actual sink to this node with arcs of zero travel time and infinite capacity. It is assumed that at $t = T$, the supply at node l will be equal to the total supply, $B = \sum_{k_i \in K} \sum_{t=1}^{T} b_{k_i}(t)$, so that $b_l(T) = -B$. This does not prevent the flow from arriving at the sink at an earlier time. When flow arrives before time *T*, it simply waits without penalty until time *T* to satisfy the demand. Supplies at transshipment nodes are zero at all times. It is assumed that the arc travel time and capacity and supply at the source nodes are known *a priori*.

3.2.2 Mixed integer programming formulation

The BEPSI is formulated as a mixed integer linear program. Decision variable $x_{ij}(t)$

represents the rate of flow that leaves node i at time t along arc (i, j), and is a continuous variable, while binary variable $\lambda_{ij}(t)$ determines the arcs to be selected. The flow $x_{ij}(t)$ arrives at node j at time $t+\tau_{ij}(t)$. The set of arcs directed in and out of a node i are given by $\Gamma^{-}(i)=\{j|(j,i)\in A\}$ and $\Gamma^{+}(i)=\{j|(i,j)\in A\}$, respectively. The BEPSI is formulated as follows.

P: $$\min \sum_{(i,j)\in A}\sum_{t\in\{0,\dots,T\}} \tau_{ij}(t)x_{ij}(t) \tag{1}$$

subject to :

$$\sum_{j\in\Gamma^{+}(i)} x_{ij}(t) - \sum_{j\in\Gamma^{-}(i)}\sum_{\{\bar{t}|\bar{t}+\tau_{ji}(\bar{t})=t\}} x_{ji}(\bar{t}) = b_i(t), \qquad \forall i\in N, t\in\{0,\dots,T\} \tag{2}$$

$$\lambda_{ij}(t)\le x_{ij}(t)\le \lambda_{ij}(t)u_{ij}(t), \qquad \forall (i,j)\in A, t\in\{0,\dots,T\} \tag{3}$$

$$\sum_{j\in\Gamma^{+}(i), j\neq i} \lambda_{ij}(t)\le 1, \qquad \forall i\in N\setminus l, t\in\{0,\dots,T\} \tag{4}$$

$$x_{ij}(t)\ge 0, \lambda_{ij}(t)\ binary, \qquad \forall (i,j)\in A, t\in\{0,\dots,T\} \tag{5}$$

In this model, the objective function (1) seeks to minimize the total time to send all flow from the source nodes to the sink. The mapping $x: A\times\{0,\dots,T\}\to Z_0^{+}$ is said to be a feasible solution if it satisfies four sets of constraints, i.e. flow conservation constraints (2), capacity constraints (3), shared information constraints (4), and nonnegativity constraints (5). Constraints (2) were first proposed by Miller-Hooks and Stock Patterson (2004) to model flow conservation constraints for the time-dependent quickest flow problem (TDQFP) (where flows are permitted to split at all nodes). Similar constraints are proposed in Tjandra (2003) for addressing the multi-source version of the TDQFP. Constraints (3) are logical constraints that impose lower and upper bounds on the flow that can pass through each arc at a given departure time. The bounds depend on the choice of arcs that will contribute to the solution paths and aid in prohibiting splittable flows. Constraints (4) allow splittable flows if the flow is split between a single outgoing arc and the holdover arc at that node. Problem (P) can be viewed as the multi-source version of the TDQFP with side constraints. Solution of the TDQFP may result in split flows at source and intermediate nodes.

3.2.3 Complexity

In this section, it is shown that problem (P) corresponding to the BEPSI is NP-hard.

Theorem 1. The evacuation problem with shared information, with or without storage of flow at intermediate nodes, is NP-hard in the strong sense ($M > 1$).

Proof. We prove this by a reduction from the Three-Partition problem, which is NP-complete in the strong sense (Garey and Johnson, 1979).

Three-Partition Problem (3-Partition): Given a set of $3n$ items, $n \in Z^+$, with associated sizes $b_1, ..., b_{3n} \in Z^+$ that satisfy $\frac{B}{4} \le b_i \le \frac{B}{2}$ and $\sum_{i=1}^{3n} b_i = nB$ for some bound $B \in Z^+$. The task is to decide whether or not the set can be partitioned into n disjoint sets $S_1, S_2, ..., S_n$ such that for $j \in \{1, ..., n\}$, $\sum_{i \in S_j} b_i = B$.

Given an instance of 3-Partition, a network can be constructed with multiple sources $a_1, ..., a_{3n}$ and single sink *l*, as shown in Figure 3-1, in polynomial time.

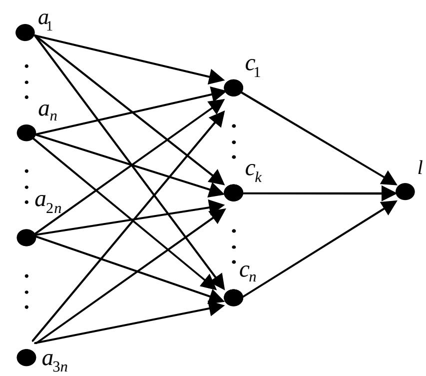


Figure 3-1 Reduction from 3-Partition

Supply associated with each source node a_i is b_i such that $\sum_{i=1}^{3n} b_i = nB$. Note that supply is assumed to be available at time 0. All arcs in the network have unit transit time. Without loss of generality, time bound $T := 2$.

Arc capacities are defined by: $u(a_i, c_k) := b_i$ for $i \in \{1,...,3n\}$ and $k \in \{1,...,n\}$ and $u(c_k, l) := B$ for $k \in \{1,...,n\}$.

It is shown that a set of routes along which nB units of flow can be shipped from sources $a_1,...,a_{3n}$ to sink *l* within T, given that flow cannot be split at nodes $a_1,...,a_{3n}$, exists iff there is a yes solution to the 3-Partition instance.

If: If the underlying instance of 3-Partition is a "yes" instance, then there is a partition $S_1,...,S_n$ of $\{1,...,3n\}$ such that for $j \in \{1,...,n\}$, $\sum_{i \in S_j} b_i = B$. The set of routes can be generated by shipping b_i units along arc (a_i, c_k) for every $i \in S_k$. Then B units of flow will be sent on to the sink from node c_k. Thus, nB units of flow arrive at sink *l* at time 2.

Only if: It remains to be shown that the existence of a flow that satisfies the conditions that all units of flow leaving the same node can take only one direction and that the last unit of flow arrives at the sink no later than time T yields a feasible solution to the corresponding 3-Partition problem instance. Denote flow on any arc (a_i, c_k) at time t by $x_{(a_i,c_k)}(t)$. The binary variable $\lambda_{(a_i,c_k)}(t)$ represents that if the arc (a_i, c_k) is contained in the solution to the special instance of BEPSI problem, then

$$\sum_{i\in\{1,\ldots,3n\}} x_{(a_i,c_k)}(0) = B \text{ and } x_{(c_k,l)}(1) = B, \qquad \forall k \in \{1,\ldots,n\}$$

and $\sum_{k\in\{1,\ldots,n\}} \lambda_{(a_i,c_k)}(0) = 1, \forall i \in \{1,\ldots,3n\}$.

It follows that

$$\sum_{i\in\left\{i \middle| \lambda_{(a_i,\, c_k)}(0)=1\right\}} b_i = B, \forall k \in \{1,\ldots,n\}$$

$$\therefore S_k = \left\{i \middle| \lambda_{(a_i,c_k)}(0) = 1, i \in \{1,\ldots,3n\}\right\} \quad , \forall k \in \{1,\ldots,n\}$$

Hence, n sets of arcs that carry a positive amount of flow into node $c_k, \forall k \in \{1,\ldots,n\}$ induce the partition of n disjoint sets satisfying $\sum_{i\in S_j} b_i = B, \forall j \in \{1,\ldots,n\}$. Note that since all the arcs in the network have unit traversal time and the time bound is 2, no flow will be shipped along any holdover arc in a feasible solution of problem (P). While no holdover arcs are employed, such arcs are available, and therefore, the reduction works for both models, with and without storage. □

3.3 Exact solution technique based on Benders decomposition

The formulation (P) contains a set of integer variables representing the selection of arcs, and a set of continuous variables representing the flow along each arc. The number of variables is large, even for mid-size instances; however, this structure is suitable for mathematical decomposition. An exact algorithm based on Benders decomposition to solve Problem (P), i.e. the BEPSI, is proposed herein. Benders decomposition (Benders, 1962) has been successfully applied to solve many mixed integer programs. See, for example, Cordeau et al. (2000) and Costa (2005), both of which successfully employed Benders decomposition to solve difficult network design problems.

The original problem is reformulated using Benders decomposition into a sub-problem, a pure network flow problem containing the continuous flow variables, and a master problem containing the binary arc selection variables. Benders cuts are generated by solution of the sub-problem and are added to the relaxed master problem at each iteration, progressively constraining the relaxed master problem. The cuts reduce the number of flow variables that must be considered, even at the expense of increasing the number of constraints.

3.3.1 Benders sub-problem

Let λ be the 0-1 vector satisfying the shared information constraints (4) and let Λ be the set of valid λ. To obtain the primal sub-problem, the values of λ must be fixed. For some fixed $\tilde{\lambda} \in \Lambda$ and variables $x_{ij}(t)$, the primal sub-problem can be given as follows.

$$\mathrm{S_p}(\tilde{\lambda})\text{:} \quad \min \sum_{(i,j)\in A} \sum_{t\in\{0,\ldots,T\}} \tau_{ij}(t) x_{ij}(t) \tag{6}$$

subject to :

$$\sum_{j\in\Gamma^{+}(i)} x_{ij}(t) - \sum_{j\in\Gamma^{-}(i)} \sum_{\{\bar{t} \mid \bar{t}+\tau_{ji}(\bar{t})=t\}} x_{ji}(\bar{t}) = b_i(t), \qquad \forall i \in N, t \in \{0,\ldots,T\} \tag{7}$$

$$\tilde{\lambda}_{ij}(t) \le x_{ij}(t) \le \tilde{\lambda}_{ij}(t) u_{ij}(t), \qquad \forall (i,j) \in A, t \in \{0,\ldots,T\} \tag{8}$$

$$x_{ij}(t) \ge 0 \text{ and integer} \qquad \forall (i,j) \in A, t \in \{0,\ldots,T\} \tag{9}$$

Since $\tilde{\lambda}_{ij}(t)$ is a constant in this formulation, constraints (8) become simple lower and upper bounds on the $x_{ij}(t)$ variables. The selection of arcs is made in solving the relaxed master problem. Thus, all that remains is to determine the amount of flow to ship along these arcs. The lower bounds on $x_{ij}(t)$ variables can be dropped without impacting the optimal solution of problem (P). Due to the fact that the objective function does not contain the $\lambda_{ij}(t)$ variables, the optimal solution (λ^*, x^*) for the relaxed problem (without lower bounds) can be used to construct an optimal solution $(\hat{\lambda}^*, x^*)$ for problem (P) with the same objective function value. It was observed in preliminary experiments that computational complexity is reduced by dropping the lower bounds. In addition, arc set $A = \{(i, j) | i, j \in N\}$ can be partitioned into the following three disjoint sets:

$I_1(A) = \{(i, j) | i, j \in N \text{ and } \Gamma^+(i) \geq 2\}$,

$I_2(A) = \{(i, j) | i, j \in N \text{ and } \Gamma^+(i) = 1\}$, and

$I_3(A) = \{(i, i) | i \in N\}$.

Thus, $A = I_1(A) \cup I_2(A) \cup I_3(A)$. The sub-problem ($\mathrm{S_p}(\tilde{\lambda})$) can be rewritten as:

$\mathrm{RS_p}(\tilde{\lambda})$**:**

$$\min \sum_{(i,j)\in A} \sum_{t\in\{0,\ldots,T\}} \tau_{ij}(t) x_{ij}(t) \tag{6}$$

subject to :

$$\sum_{j\in\Gamma^+(i)} x_{ij}(t) - \sum_{j\in\Gamma^-(i)} \sum_{\{\bar{t} | \bar{t}+\tau_{ji}(\bar{t})=t\}} x_{ji}(\bar{t}) = b_i(t), \qquad \forall i \in N, t \in \{0,\ldots,T\} \tag{7}$$

$$x_{ij}(t) \leq \tilde{\lambda}_{ij}(t) u_{ij}(t), \qquad \forall (i, j) \in I_1(A), t \in \{0,\ldots,T\} \tag{8a}$$

$$x_{ij}(t) \leq u_{ij}(t), \qquad \forall (i, j) \in I_2(A), t \in \{0,\ldots,T\} \tag{8b}$$

$$x_{ij}(t) \geq 0 \text{ and integer} \qquad \forall (i, j) \in A, t \in \{0,\ldots,T\} \tag{9}$$

Sub-problems ($\mathrm{RS_p}(\tilde{\lambda})$) and ($\mathrm{S_p}(\tilde{\lambda})$) are equivalent mathematical descriptions; however, significant improvement in computational performance of the Benders decomposition approach can be obtained by using ($\mathrm{RS_p}(\tilde{\lambda})$) in place of ($\mathrm{S_p}(\tilde{\lambda})$). Sub-problem ($\mathrm{RS_p}(\tilde{\lambda})$) has a pure network flow structure and the constraint matrix is totally unimodular. Hence, the optimal solution can be obtained by solving the linear programming (LP) relaxation or its dual.

The dual of the LP relaxation of the primal sub-problem, called the dual sub-problem, is given as problem ($\mathrm{DRS_p}(\tilde{\lambda})$) as follows.

$\mathrm{DRS_p}(\tilde{\lambda})$:

$$\text{Max} \quad \sum_{t\in\{0,\ldots,T\}} \left(\sum_{i\in N} \pi_i(t) b_i(t) + \sum_{(i,j)\in I_2(A)} u_{ij}(t) m_{ij}(t) + \sum_{(i,j)\in I_1(A)} \tilde{\lambda}_{ij}(t) u_{ij}(t) m_{ij}(t) \right) \tag{10}$$

subject to :

$$\pi_i(t) - \pi_j\left(t+\tau_{ij}(t)\right) + m_{ij}(t) \le \tau_{ij}(t), \qquad \forall (i,j)\in A\setminus I_3(A), t\in\{0,\ldots,T\} \tag{11}$$

$$m_{ij}(t) \le 0, \qquad \forall (i,j)\in A\setminus I_3(A), t\in\{0,\ldots,T\} \tag{12}$$

Here, $\pi_i(t)$ for $i\in N$ and $t\in T$ are the dual variables associated with constraints (7) and $m_{ij}(t)$ for $i\in N$ and $t\in T$ are the dual variables associated with constraints (8a) and (8b). Let *D* denote the polyhedron defined by constraints (11) and (12), and let P_D and R_D be the complete sets of extreme points and extreme rays of *D*, respectively. The null vector 0 satisfies constraints (11) and (12); thus, the dual sub-problem is always feasible. By the weak duality theorem, the primal sub-problem is either infeasible or feasible and bounded if the dual is feasible. To exclude the possibility of primal infeasibility, the following inequality must hold:

$$\sum_{t\in\{0,\dots,T\}}\left(\sum_{i\in N}\pi_i(t)b_i(t)+\sum_{(i,j)\in I_2(A)}u_{ij}(t)m_{ij}(t)+\sum_{(i,j)\in I_1(A)}\tilde{\lambda}_{ij}(t)u_{ij}(t)m_{ij}(t)\right)\le 0, \quad \forall(\pi,m)\in R_D \quad .$$

If the dual sub-problem is bounded and the primal sub-problem is feasible, the optimal value of both problems is then given by

$$\operatorname*{Max}_{(\pi,m)\in P_D} \quad \sum_{t\in\{0,\dots,T\}}\left(\sum_{i\in N}\pi_i(t)b_i(t)+\sum_{(i,j)\in I_2(A)}u_{ij}(t)m_{ij}(t)+\sum_{(i,j)\in I_1(A)}\tilde{\lambda}_{ij}(t)u_{ij}(t)m_{ij}(t)\right).$$

3.3.2 Benders relaxed master problem

The Benders master problem is obtained by replacing constraints (2), (3) and (4) by Benders cuts (14) and (15). Constraints (14) are optimality cuts that ensure corresponding non-optimal solutions are excluded. Constraints (15) are feasibility cuts that ensure the resulting primal sub-problem is feasible. Introducing the additional free variable *Z*, problem (P) can be reformulated as the following equivalent problem ($\overline{\mathrm{P}}$).

($\overline{\mathrm{P}}$): $\quad \min \quad Z \qquad (13)$

subject to :

$$Z-\sum_{t\in\{0,\dots,T\}}\sum_{(i,j)\in I_1(A)}u_{ij}(t)m_{ij}(t)\lambda_{ij}(t)\ge\sum_{t\in\{0,\dots,T\}}\left(\sum_{i\in N}\pi_i(t)b_i(t)+\sum_{(i,j)\in I_2(A)}u_{ij}(t)m_{ij}(t)\right),$$

$$(\pi,m)\in P_D \qquad (14)$$

$$\sum_{t\in\{0,\dots,T\}}\sum_{(i,j)\in I_1(A)}u_{ij}(t)m_{ij}(t)\lambda_{ij}(t)\le-\sum_{t\in\{0,\dots,T\}}\left(\sum_{i\in N}\pi_i(t)b_i(t)+\sum_{(i,j)\in I_2(A)}u_{ij}(t)m_{ij}(t)\right),$$

$$(\pi,m)\in R_D \qquad (15)$$

$$\sum_{j\in\Gamma^+(i),\, j\ne i}\lambda_{ij}(t)\le 1, \qquad \forall i\in N\setminus l,\ t\in\{0,\dots,T\} \qquad (16)$$

$$\lambda_{ij}(t)\ binary, \qquad \forall(i,j)\in A,\ t\in\{0,\dots,T\} \qquad (17)$$

Constraints (14) and (15) need not be enumerated exhaustively, because most of the constraints will be inactive in the optimal solution. Thus, a relaxation of problem ($\overline{\mathrm{P}}$) can be obtained by dropping constraints (14) and (15) and iteratively adding them to the relaxation until optimality is achieved. Results of preliminary experiments show that when beginning with $R_D = \varnothing$, resulting sub-problems are likely to be infeasible and Benders decomposition may be very slow to converge. This concern is addressed by augmenting the relaxed master problem with valid, stronger inequalities that can reduce the number of iterations required to reach optimality.

Proposition 1. In FIFO[1] networks, if in the optimal solution to the BEPSI, flow is shipped from node *i* ($i \neq l$) at time *t* along a holdover arc, then

$$\sum_{j \in \Gamma^+(i),\, j \neq i} \lambda_{ij}(t) = 1,\ \forall t \in \{0,\ldots,T-1\}.$$

Discussion. Let $\left\{x_{ij}(t)\right\}_{\forall (i,j)\in A, t\in\{0,\ldots,T-1\}}$ and $\left\{\lambda_{ij}(t)\right\}_{\forall (i,j)\in A, t\in\{0,\ldots,T-1\}}$ be the optimal solution. Suppose that in this solution, $\lambda_{ii}(t)=1$ and $\sum_{j\in\Gamma^+(i),\, j\neq i} \lambda_{ij}(t)=0$ for some node *i* ($i \neq l$) at time *t*. Without loss of generality, suppose that $\lambda_{ij}(t+1)=1, j\in\Gamma^+(i)$ and $j \neq i$. Then a new solution can be constructed where $\lambda_{ii}(t)=0$, $\lambda_{ij}(t)=1$, $\lambda_{jj}(t+\tau_{ij}(t))=1$, constraints (2)-(5) are satisfied and the objective function value is lower than in the optimal solution (because the arc traversal times cannot improve over time), contradicting the assumption that the original solution is optimal. □

According to proposition 1, for any node *i* ($i \neq l$) at time *t*, $\sum_{j\in\Gamma^+(i),\, j\neq i} \lambda_{ij}(t) \geq \lambda_{ii}(t)$ holds.

[1] A FIFO (First-In, First-Out) network ensures that one can never arrive earlier by departing later when traveling along the same path.

Constraints (18a) and (18b) represent the relationship between inflow and outflow in the FIFO network (capacities are usually deteriorating in the evacuation problem), where σ is the maximum in-degree for any *i* in *N*.

$$\sigma \sum_{j \in \Gamma^{+}(i), j \neq i} \lambda_{ij}(t) - \sum_{j \in \Gamma^{-}(i)} \sum_{\{\bar{t} | \bar{t} + \tau_{ji}(\bar{t}) = t\}} \lambda_{ji}(\bar{t}) \geq 0 \;\; , \forall\, i \in N \setminus l, t \in \{0,...,T\}, \quad \text{and} \tag{18a}$$

$$- \sum_{j \in \Gamma^{+}(i), j \neq i} \lambda_{ij}(t) + \sum_{j \in \Gamma^{-}(i)} \sum_{\{\bar{t} | \bar{t} + \tau_{ji}(\bar{t}) = t\}} \lambda_{ji}(\bar{t}) \geq 0 \;\; , \forall i \in N \setminus l, t \in \{0,...,T\}, \tag{18b}$$

In addition, the concept of Pareto-optimal cuts is employed. Similar to other network flow problems, sub-problem ($\mathrm{RS_p}(\tilde{\lambda})$) is often degenerate and there may exist multiple optimal solutions which lead to different optimality cuts. Pareto-optimal cuts were defined as any cut that is not dominated by any other cut in Magnanti and Wong (1981). By employing a Pareto-optimal cut in place of an optimality cut obtained from any optimal solution that is identified, a stronger cut may be obtained. As applied to solving sub-problem ($\mathrm{RS_p}(\tilde{\lambda})$), the Pareto-optimal cuts can be generated by solving the following auxiliary dual sub-problem:

$$\text{Max} \quad \sum_{t \in \{0,...,T\}} \left(\sum_{i \in N} \pi_i(t) b_i(t) + \sum_{(i,j) \in I_2(A)} u_{ij}(t) m_{ij}(t) + \sum_{(i,j) \in I_1(A)} \lambda^{0}_{ij}(t) u_{ij}(t) m_{ij}(t) \right) \tag{19}$$

$$s.t. \quad \sum_{t \in \{0,...,T\}} \left(\sum_{i \in N} \pi_i(t) b_i(t) + \sum_{(i,j) \in I_2(A)} u_{ij}(t) m_{ij}(t) + \sum_{(i,j) \in I_1(A)} \tilde{\lambda}_{ij}(t) u_{ij}(t) m_{ij}(t) \right) = Z(\tilde{\lambda}) \tag{20}$$

$$(\pi, m) \in \Omega \tag{21}$$

where $\{\lambda^{0}_{ij}(t)\}$ is a core point of Λ and $Z(\tilde{\lambda})$ is the optimal objective value of problem ($\mathrm{DRS_p}(\tilde{\lambda})$). Constraint (20) ensures that the Pareto-optimal solution determined by solving this dual sub-problem corresponds with an alternative optimal solution to sub-problem ($\mathrm{DRS_p}(\tilde{y})$). Constraint (21) is equivalent to constraints (11) and (12).

Instead of solving the auxiliary dual problem directly, one can solve its primal problem, which is equivalent to primal sub-problem ($\mathrm{RS_p}(\tilde{y})$) with an additional variable and minor changes in the right-hand side values. This approach is due to Magnanti and Wong (1981).

3.3.3 Benders decomposition algorithm

Once problem (P) has been reformulated as in Section 3.3.2, the Benders decomposition algorithm can be applied iteratively over the relaxed master and sub-problems until convergence. The algorithm begins by solving the relaxed master problem to determine those arcs along which flow will be shipped, i.e. the necessary input for solution of the sub-problem. Let *s* represent the iteration number. Let $P_{sD} \subset P_D$ represent a restricted set of extreme points and $R_{sD} \subset R_D$ a restricted set of extreme rays. Problem ($\overline{\mathrm{P}}^s$) is obtained by replacing P_D and R_D with P_{sD} and R_{sD} in iteration *s*. Sets P_{sD} and R_{sD} are determined from solution of the sub-problem from iterations 1 to *s*. Each of these extreme points or extreme rays produces a Benders cut. These cuts are iteratively added to the relaxed master problem during the execution of the Benders decomposition algorithm.

Problem ($\overline{\mathrm{P}}$) can be relaxed further: It is not necessary to generate all constraints (16). If constraints (16) in problem ($\overline{\mathrm{P}}$) were relaxed, a subset of nodes may contain flow that splits in the optimal solution to this relaxed problem. For many problem instances, this subset is relatively small in comparison to the number of nodes. Since computational effort significantly increases with the number of constraints (16), and since many of these constraints will be inactive at optimality, those constraints that are violated in an iteration can be added to the relaxed master problem iteratively. This procedure is summarized in step 3 of the BD algorithm, which is described next.

Algorithm BD

Step 1: Set $t := 1$. Solve problem $\mathrm{RS_p}(\tilde{\lambda})$, where $\tilde{\lambda}$ is a 1's vector. Let Ω^1 be the set of nodes where flow splits.

Step 2: Set $s := 1$, $P_{1D}^1 := \varnothing$, $R_{1D}^1 := \varnothing$.

Step 2.1: Solve problem ($\overline{\mathrm{P}}_s^t$). If it has no feasible solution, stop; otherwise, let λ_s^t be an optimal solution of objective function value Z_s^t.

Step 2.2: Solve problem $\mathrm{RS_p}(\lambda_s^t)$.

If the problem is finite, let x_s^t be a primal optimal solution, let $(\pi, m)_s^t$ be a dual optimal solution, and let $z\left(\lambda_s^t\right)$ be the objective function value of sub-problem. If $Z(\lambda_s^t) \le Z_s^t$, then $\left(x_s^t, \lambda_s^t\right)$ is an optimal solution to the master problem with constraints set Ω^1, and go to step3; otherwise, set $P_{s+1,D}^t := P_{sD}^t \cup \left\{(\pi, m)_s^t\right\}$, $R_{s+1,D}^t := R_{sD}^t$, $s := s+1$, and return to step 2.1.

If the sub-problem is infeasible, let $(\pi, m)^s$ be a dual extreme ray such that

$$\sum_{t \in \{0,\dots,T\}} \sum_{(i,j) \in I_1(A)} u_{ij}(t) m_{ij}(t) \lambda_{ij}(t) \le -\sum_{t \in \{0,\dots,T\}} \left(\sum_{i \in N} \pi_i(t) b_i(t) + \sum_{(i,j) \in I_2(A)} u_{ij}(t) m_{ij}(t) \right)$$

Set $R_{s+1,D}^t := R_{SD}^t \cup \left\{(\pi, m)_s^t\right\}$, $P_{s+1,D}^t := P_{sD}^t$, $s := s+1$, and return to step 2.1.

Step 3: If $\left(x_s^t, \lambda_s^t\right)$ satisfies constraints (16), $\left(x_s^t, \lambda_s^t\right)$ is the optimal solution to the original problem (P), **stop**; Let N^t be the set of nodes where shared information constraints (16) are violated. Set $\Omega^{t+1} := \Omega^t \cup N^t$, $t := t+1$, and go to step 2.

The *BD* algorithm terminates with the optimal solution (Z_p) to problem (P). Step 2 ensures that $\left(x_s^t, \lambda_s^t\right)$ is a feasible solution to problem (P), such that $Z(\lambda_s^t) \geq Z_p$ will hold. $\left(\lambda_s^t, Z_s^t\right)$ is an optimal solution to the relaxation of problem ($\overline{\mathrm{P}}$). Hence, $Z_s^t \leq Z_p$ and if $Z(\lambda_s^t) \leq Z_s^t$, then $Z(\lambda_s^t) = Z_s^t = Z_p$. Thus, as long as problem (P) is feasible, the algorithm will always terminate with an optimal solution $\left(x_s^t, \lambda_s^t\right)$. It is well known that such Bender's decomposition algorithms have exponential worst-case computational complexity, because it is possible that in the worst-case all the extreme points and extreme rays of ***D*** will be enumerated.

3.3.4 Example to illustrate nature of solution

The solution of a small problem instance is shown to illustrate the nature of solutions to the BEPSI and to distinguish such solutions from typical solutions of other related network flow problems.

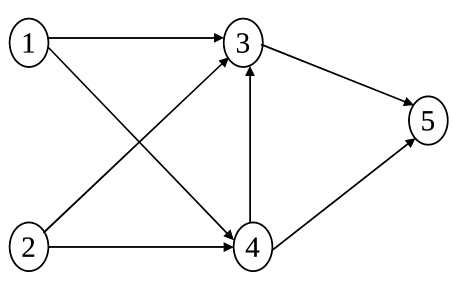


Figure 3-2 Example network

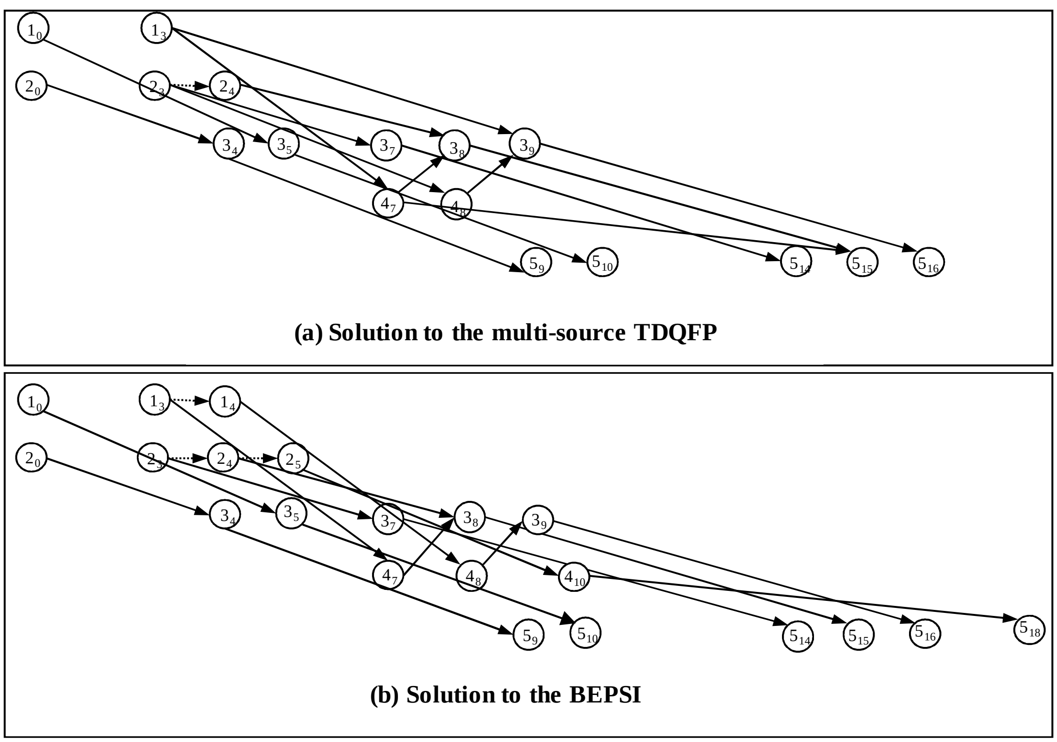
Specifically, solution to the BEPSI by the BD algorithm presented in Section

3.3.3 is compared with solution to the TDQFP by the extension of the TDQFP algorithm for multiple sources on a small time-dependent network given in Figure 3-2.

Table 3-1 Time-dependent travel times and capacities of example in Figure 3-2

(i, j)	(1, 3)	(1, 4)	(2, 3)	(2, 4)	(3, 5)	(4, 3)	(4, 5)
$\tau_{ij}(t)$	5,t = 0 6,1≤t≤20	4, 0≤t≤5 6, 6≤t≤20	4, 0≤t≤4 6, 5≤t≤20	4, 0≤t≤1 5, 2≤t≤10 7, 11≤t≤20	5, 0≤t≤6 7, 7≤t≤19 9, t = 20	1, 0≤t≤14 3, 15≤t≤20	6, 0≤t≤3 8, 4≤t≤20
$u_{ij}(t)$	20, 0≤t≤2 15,3≤t≤20	20, 0≤t≤1 15, 2≤t≤6 10, 7≤t≤20	20, 0≤t≤1 10, 2≤t≤20	20, 0≤t≤2 15, 3≤t≤20	25, 0≤t≤2 20,3≤t≤20	20, 0≤t≤9 18, 10≤t≤17 15, 18≤t≤20	25, 0≤t≤12 20, 13≤t≤20

Assume that $T = 20$, $b_1(0) = 10$, $b_2(0) = 15$, $b_1(3) = 20$, $b_2(3) = 25$, $b_5(T) = -70$ and $b_i(t) = 0$, otherwise. A holdover arc, (i,i), exists at each $i \in N$. The time-dependent link traversal times and capacities are given in Table 3-1. Recall that for all $t \in \{0,...,T\}$ and $i \in N \setminus l$, $\tau_{ii}(t) = 1$ and $u_{ii}(t) = \infty$.



(a) Solution to the multi-source TDQFP

(b) Solution to the BEPSI

Figure 3-3 Final solutions to the time-dependent evacuation problem with and without shared information constraints

The resulting solution to the BEPSI and related TDQFP are illustrated in Figure 3-3 on a time-expanded network. The time-expanded network is created by making copies of the original network for each discrete interval of time. The numbers correspond to physical node numbers and their subscripts represent the departure time intervals, e.g. 2_4 represents node 2 at time 4. Waiting arcs are shown as dashed lines and are defined at every node between every consecutive pair of departure times. The example illustrates that the TDQFP solution may be infeasible for the BEPSI. In the solution to the BEPSI (Figure 3-3(b)), the last unit of flow exits the network at time 18. Since a solution exists for which it is possible that, for a greater total time, the time by which the last unit of flow exits the network can be reduced (i.e. from 18 to 17 units of time via 4_9 from node 2_4), it can be shown that triple optimization results given in Jarvis and Ratliff (1982) for a set of dynamic flow problems do not hold for the BEPSI. Specifically, optimal solution of the BEPSI is not necessarily optimal for an equivalent problem that seeks the minimum time by which the last unit exits the network in place of minimizing total time.

The evacuation time (i.e. the time until the last unit egresses) is 16 units for the multi- source TDQFP and 18 units for the BEPSI. The TDQPF solution contains three nodes (nodes 1_3, 2_3 and 4_7) at which flow is split and is, therefore, an infeasible solution to the BEPSI.

Proposition 2. The value of the optimal solution to the multi-source TDQFP provides a lower bound on the value of the optimal solution to the BEPSI.

Discussion. The feasible region of the BEPSI is contained in the feasible region of the multi-source TDQFP and, is thus, more restrictive than that of the multi-source TDQFP. Hence, the value of the optimal solution to the multi-source TDQFP provides a lower bound on the value of the optimal solution to the BEPSI. □

3.4 Computational experiments

Results of computational experiments conducted on a network representation of an existing, four-story building, the A. V. Williams Building, on the University of Maryland campus are given in this section. Data for the building was collected on-site, taking actual measurements of doorways, corridor widths and lengths, stairwell widths, and other dimensions. The layout of the four floors was similar; thus, data was only collected on the second floor and was replicated to create the network model of the four-story building. The layout of the second floor is shown in Figure 3-4.

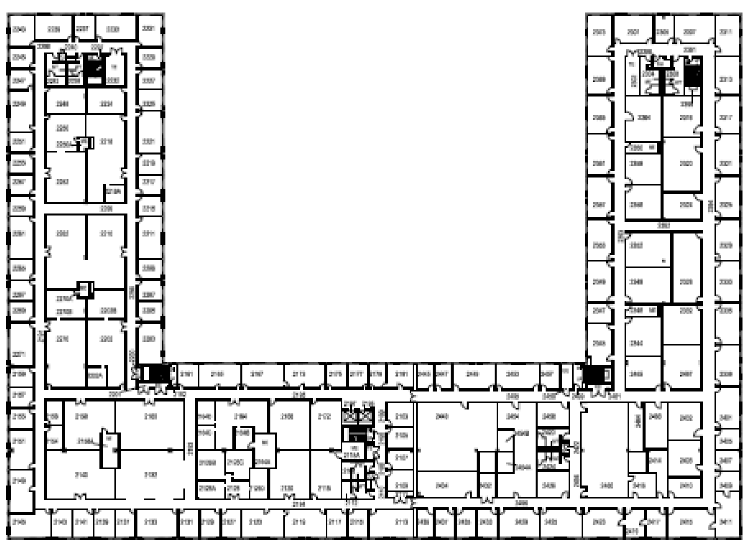


Figure 3-4 The A. V. Williams Building second floor layout

3.4.1 Experimental design

A network representation of the A. V. Williams Building was developed by placing nodes on each side of each doorway connected by an edge to allow the movement of people between rooms and corridors, into and out of stairwells and through the exits and by placing nodes at the intersection of corridors. The nodes in the corridors were connected by edges. Edges were also used to represent stairwells. Elevators were ignored, because use of elevators in this building is prohibited during an evacuation. It was further assumed that escape from the first floor was only possible through doorways; no window egress was modeled. This resulted in a 612-node, 1,480-edge network with five exit nodes. The maximum occupancy related to the classrooms, offices, laboratories and lavratories permitted by fire codes were estimated with the use of the 2000 edition of the NFPA 101 Life Safety Code (2001).

The amount of supply (i.e. evacuees) at each node is set based on variations of the maximum occupancies of the rooms in the building as per the NFPA Life Safety Code. Three levels of supply are considered (average, maximum and maximum plus), where the maximum plus category introduces exceptional supply levels at a subset of critical nodes.

Two approaches were considered for estimating flow rates that can be translated to travel times and capacities associated with the edges. The first is to calculate the saturated flow rate from empirical formulae that have been proposed in the literature (see, for example, Chalmet et al., 1982). The second is to use values related to pedestrian movement characteristics provided in the SFPE Handbook of Fire Protection Engineering (1988). The latter approach was employed in estimating these values for the A. V. Williams Building. These estimates are provided in Table 3-2.

Table 3-2 Crowd movement parameters for various facilities*

Facility	Density (person/ft^2)	Speed (ft/min)	Flow (person/min/ft)
Doorway	0.22	120	26
Pathway	0.20	120	24
Stairwell	0.19	95	18

* DiNenno et al. (1988)

Edge capacities were set to the maximum flow rate as computed from rates given in Table 3-2. The time interval duration for time discretization was assumed to be one minute. Speeds were employed to estimate edge travel times.

Six scenarios were considered in tests of the BD algorithm for solving the BEPSI that were conducted on the network representation of the A. V. Williams Building. The factors that were considered in the construction of these scenarios include the number of people present at the time of the initiation of the evacuation (i.e. supply at the source nodes), whether or not corridors and stairwells were blocked or impaired (i.e. whether or not edges were operating at maximum capacity and maximum speeds could be reached), and the type and location of the event triggering the evacuation.

In the first two scenarios, conditions were assumed to be ideal, as would be the case in a fire drill as opposed to an actual fire. Conditions were, therefore, assumed to be time-invariant. Multiplication factors were applied to this ideal scenario in the remaining three scenarios to replicate conditions that were worsening over time. The multiplication factors are cumulatively applied from one time interval to the next to both capacities and travel times and are given in Table 3-3. The application of these factors is designed to replicate conditions that are worsening over time, i.e. that are FIFO in nature (there is no benefit in terms of egress time to wait for better conditions at later time intervals).

Scenarios are designed such that the scale of the hazard that initiated the need for the evacuation and its impact increase with increasing scenario identification number. In scenarios 3 to 5, conditions are assumed to be worse than those of the ideal scenarios (scenario 1 and 2), but no specific hazard location is simulated. However, in scenario 6, the hazard is assumed to occur at a location that results in untenable conditions or blockages along major escape pathways. In this scenario, it is assumed that a fire begins in the west wing of the fourth floor. Conditions deteriorate rapidly. One corridor in the west wing is blocked and the nearest stairwell is impassable.

Table 3-3 Characteristics of test scenarios

Scenario	Capacities	Travel times	Supply level	Severity of Conditions
1	1	1	1	Ideal conditions
2	1	1	3	Ideal conditions
3	0.98	1.02	1	Slightly impacted
4	0.98	1.02	2	Slightly impacted
5	0.96	1.04	3	Impacted
6	0.95	1.06	3	Severely impacted, some links disabled

In all six scenarios, time horizon T was assumed to be 20 minutes and stairwells and corridors were assumed to be empty at initiation of the evacuation. Results from application of the BD algorithm on the A. V. Williams Building under these six scenarios are discussed next.

3.4.2 Result Analysis

The BD algorithm was implemented in Microsoft Visual Studio C++ 6.0 language with the ILOG CPLEX callable library 9.1 (2005) and was run on a personal computer with Pentium (4) CPU 3.20 GHz and 2.00 GB of RAM.

Valid cuts (18) are added to the Benders master problem ($\bar{\text{P}}$) to accelerate convergence to the optimal solution. At each step, where an optimality cut is desired, a Pareto-optimal cut is generated. It was observed in the experiments that these cuts led to quick convergence on the optimal solution. For most of the problem instances that were tested, the number of iterations and computation time were reduced considerably by the inclusion of the Pareto-optimal cuts as compared with runs in which these cuts were not employed. Additional computational improvements might be obtained by relaxing integrality constraints on the variables of the relaxed master problem and generating Benders cuts from fractional solutions as was proposed by McDaniel and Devine (18). McDaniel and Devine showed that exact solution of the relaxed master problem was not required at each step and noted that any feasible solution can generate Benders cuts.

The results of experiments showed that there is a significant reduction in computational time obtained by using sub-problem ($\text{RS}_\text{p}(\tilde{x})$) instead of ($\text{S}_\text{p}(\tilde{x})$). CPU times were reduced by a factor of at least 10 for all tested cases. Either a generic MIP solver or specially designed algorithms, such as the TDQFP algorithm, can be employed to solve ($\mathrm{RS_p}(\mathcal{X})$).

An alternative to the BD algorithm is to employ a branch-and-cut algorithm based on a similar concept to the relaxation step employed in the BD algorithm (i.e. step 3). As illustrated in the example in Section 3.3.4, solution of TDQFP may result in split flows at one or more locations. Let the set of the nodes where flow splits in the TDQFP solution be $S^0(N) \subset N$. A set of constraints can be generated to enforce unsplittable flow as follows.

$$\sum_{j \in \Gamma^+(i),\, j \neq i} x_{ij} / u_{ij} \leq 1, \qquad \forall i \in S^0(A). \tag{21}$$

If the current solution violates cuts (21), then the cuts are valid. Repeat the process until no valid cut can be generated. Once a solution is obtained that does not violate cuts (21), branch on the x_{ij} variables that violate the shared information constraints (4), i.e. impose the disjunction $\left(x_{ij^1} = 0\right) \vee \left(x_{ij^2} = 0\right) \vee \ldots \vee \left(x_{ij^s} = 0\right)$, where $x_{ij^1}, x_{ij^2}, \ldots, x_{ij^s} \in \{x_{ij} \,|\, x_{ij} > 0, \forall i \in S^0(A)\}$. The number of branches s is equal to the number of arcs with positive flow departing from the same node at the same time.

Table 3-4 Computational results on the real network

<table>
<tr><th rowspan="3">Scenario</th><th rowspan="3">$\Delta(Z_{BEPSI} - Z_{TDQFP})$</th><th rowspan="3">Number of cuts</th><th colspan="3">Computational time (CPU seconds)</th></tr>
<tr><th colspan="2">BD</th><th rowspan="2">Branch-and-Cut</th></tr>
<tr><th>To 95% optimality</th><th>To optimality</th></tr>
<tr><td>1</td><td>0</td><td>4</td><td>-</td><td>3.0</td><td>4.6</td></tr>
<tr><td>2</td><td>0</td><td>4</td><td>1.6</td><td>3.3</td><td>21.7</td></tr>
<tr><td>3</td><td>0</td><td>12</td><td>1.9</td><td>30.8</td><td>80.0</td></tr>
<tr><td>4</td><td>32</td><td>36</td><td>6.0</td><td>31.2</td><td>178.7</td></tr>
<tr><td>5</td><td>0</td><td>32</td><td>19.6</td><td>58.5</td><td>221.3</td></tr>
<tr><td>6</td><td>224</td><td>44</td><td>17.7</td><td>94.8</td><td>>0.5h</td></tr>
</table>

The computational time required by the BD algorithm, as well as the branch-and-cut technique, for solving the BEPSI in the A.V. Williams Building is provided in Table 3-4. The scenario number as defined in Table 3-3 is given in the first column. The second column reports the difference between the optimal objective function value to the BEPSI, containing shared information constraints, and the TDQFP (extended for multiple origins), where the shared information constraints are dropped. The third column reports the number of iterations, i.e. number of Benders cuts. The fourth and fifth columns report the computational time in CPU seconds used by the BD algorithm to reach 95% of optimality and optimality, respectively. The sixth column reports the computational time required by the branch-and-cut algorithm to reach optimality. All reported times include all input and output time.

Results show that as the problem becomes more difficult and waiting arcs are required, the required computational time to solve the problem to optimality by either approach increases. The more frequent flow splits in the TDQFP solution, the greater the computational effort required by the BD and branch-and-cut algorithms. It is also postulated that the performance of both algorithms will be impacted by the degree of each node, as the larger the degree, the more likely flow is to split. The required computational time of the BD algorithm increases less than linearly with increasing supply and deteriorating network conditions. Moreover, the computational time required to achieve 95% of optimality is significantly less than that required to achieve optimality. Since the BD algorithm can be prematurely terminated with a feasible solution, stopping the algorithm after a short period of time may be a viable alternative. In all scenarios, the BD algorithm outperforms the branch-and-cut method. Note that step 3 of the BD algorithm is specialized for this particular application. It was observed that the addition of step 3 to the BD algorithm, where only a subset of constraints (16) of problem ($\bar{P}$) are enforced, led to significant reductions in computation time. Additional experiments would be required to assess the impact of network size on the computational performance of these techniques.

In building evacuation, as new information about the current state of the building's structures and circulation systems are obtained, updates to the network model in terms of supply, arc capacities and arc traversal times will be made and a new BEPSI will need to be solved. Rather than starting from scratch, it is possible to employ the Benders cuts generated in the prior problem instance as the initial cuts in employing the BD algorithm to solve the new problem instance if the supply increases and/or arc capacities decrease. Decreases in arc capacities are expected in circumstances warranting an evacuation, as fire and smoke will spread throughout the building and collapse of the structural components will occur progressively. That is, conditions worsen with time and capacities accordingly decrease with time. Additional experiments were conducted to assess the magnitude of improvement that results from employing the Benders' cuts generated in the prior problem instance in solving the updated problem.

Changes to arc capacities and supply in Scenario 3 were considered in these additional experiments. Specifically, four updates were considered: (1) supplies at randomly chosen nodes increase, (2) supply at all supply nodes increase, (3) capacities of randomly chosen arcs decrease, and (4) capacities of all arcs decrease. One might also assess the benefits of such a reoptimization approach where changes in supply and capacities occur simultaneously. Results of runs on these versions of scenario 3 are given in Table 3-5.

The results of Table 5 show that significant (on the order of 60-70%) reductions in computational time result from solving the updated problem instance starting with the Benders' cuts generated in solving the prior problem instance (i.e. the reoptimization time) as compared with solving the new problem instance from scratch (i.e. with no information from the prior problem instance).

Table 3-5 Reoptimization results of the BD Algorithm

	Increase of supply		Decrease of Capacity	
	Select nodes	Entire network	Select arcs	Entire network
Computational time required with reoptimization (CPU seconds)	33.4	33.5	30.5	24.6
% of time required as compared to resolving from scratch	41.5%	42.0%	37.9%	30.5%

3.5 Conclusions and future research

In this chapter, the building evacuation problem with shared information (BEPSI) is formulated as a mixed integer linear program. The problem is shown to be NP-hard. An exact algorithm based on Benders decomposition is proposed for its solution. Computational experiments performed on a network representation of an actual four-story building were conducted to illustrate how the proposed procedure can be applied to solve for the optimal evacuation instructions in an actual building and to demonstrate the feasibility of its application. The solution technique is designed in such a way that it can be prematurely terminated and feasible solutions can be obtained. Experimental results show that significantly less time is required to obtain solutions that are within 95% of optimality.

By restricting flows to a single arc at each point in time and explicitly considering the inherent dynamic nature of future conditions, the resulting evacuation plans are more likely to be followed in light of our understanding of group dynamics in evacuation and to aid the evacuees in avoiding potentially high risk situations. Traditional evacuation planning techniques ignore the dynamics of a fire moving through a corridor or through a stairwell and existing optimization techniques would not prevent solutions from suggesting groups to split at the nodes. Consequently, implementation of evacuation plans developed by the proposed technique for a large building, ship or military complex can result in a reduction in the number of lost lives, trapped evacuees or rescue workers, and risk of exposure. Further, shorter egress times may result, permitting recovery efforts to begin quickly.

As presented, solution of the proposed formulation may result in flows that arrive at an intermediate location at a given point in time, but depart along different paths by departing at different departure time intervals, i.e. by definition, the flow is not split, but in practice, the flows take different paths. This type of splitting of flows is permitted through the introduction of holdover arcs that are modeled to ensure feasibility. If such holdover arcs were not permitted, it would be difficult to model situations where there is an excess of evacuees waiting to enter a chosen path with insufficient capacity to handle all evacuees who arrive in a single time interval. In an evacuation, conditions typically worsen with time; that is, the arc traversal times are FIFO, Thus, it is always best to leave as early as possible and waiting will not be chosen if it can be prevented. Additionally, capacity of the holdover arcs may be restricted and the discretization interval size can be set to a sufficiently large value to minimize the occurrence of such splitting of flows.

One might argue that arc traversal times are in reality a function of flow, similar to travel time estimation models for vehicular traffic flows. This concept of selecting paths such that flows are not split can be extended to consider flow-dependent traversal times. A similar concept is described in Köhler and Skutella (2005) with respect to the quickest flow problem."

The procedures developed through this research activity will impact many other functional areas as well, including, for example, evacuation of a geographic region due to military attack, human-made accident, or natural disaster, such as an accident involving a nuclear power plant or escape of hazardous chemicals, collapse of a structure such as dam walls, hurricane, earthquake, flooding, volcanic eruption, or tsunami. Evacuation instructions can be provided to vehicles via changeable message signs, radio, the internet, or on-board devices in suitably equipped vehicles with further development of Intelligent Transportation Systems. Moreover, as with other network flow-based techniques, it is expected that the techniques proposed herein will have application in many diverse arenas, such as production-distribution systems, fleet management, and communications.

Many theoretical and practical aspects of this problem remain to be explored. For some problem instances, or building layouts, it may be feasible to employ the TDQFP algorithm or something similar that allows splitting of flow, if the solutions are unlikely to contain split flows. Heuristic repair operators can be applied to locations of split flow to obtain feasible and potentially near-optimal solutions. Experiments on additional building designs could be conducted to assess the negative impact on total evacuation time that results from enforcing solutions that do not permit splittable flows. Finally, heuristics could be developed to more quickly obtain feasible and, hopefully, near-optimal solutions for large-size networks. The exact procedure proposed herein for this difficult problem can be used to obtain benchmark solutions, enabling evaluation of quicker, heuristic techniques.

Evacuees may not prefer the solution that optimizes functions of time, e.g. evacuation time, but instead may prefer a path with high likelihood of leading to successful escape. Alternative objectives that consider these and other issues of equity that arise in solutions for the evacuation problem have been proposed in the literature (e.g. Lin, 2001; Opasanon and Miller-Hooks, 2009). Regardless of the objective that is chosen for the determination of the optimal instructions, the issue of shared information arises. One may extend this work to address the issue of unsplittable flows in the context of other objectives, such as those related to minimization of risk.

Chapter 4 Resilience: An Indicator of Recovery Capability in Intermodal Freight Transport

4.1 Introduction

The rapid development of e-commerce, economic globalization, just-in-time production, and logistics and supply chain systems over past decades has lead to significant need for efficient and effective management of freight movements. Individuals and companies have become increasingly dependent on the freight transport system to deliver their goods. In fact, U.S. domestic freight moved by air, truck, and railroad increased by 24% between 1996 and 2005 (Bureau of Transportation Statistics, 2007). Furthermore, international trade is projected to increase by 2.8 percent annually through 2020 (Leinbach & Capineri, 2007) and freight demand is projected to increase 89 percent by 2035 as compared with 2005 (FHWA, 2008). Consequently, significant increase in demand for freight transport in coming years is anticipated. However, the freight transport sector is operating at or near its capacity in many regions of the world, including the United States (AASHTO, 2007). Despite this, there has been little increase in the capacity of the freight transport system. In fact, in the United States, the capacity of the rail freight network has decreased in past years (Larson and Spraggin, 2000). Simultaneously, risks from accidents, weather-induced hazards, and terrorist attack on the freight transport systems have dramatically increased. Thus, trucking companies, rail carriers, infrastructure managers, and terminal and port operators must invest in security measures to prevent or mitigate the effects of disasters resulting from such incidents. Even less monumental incidents, such as derailment of cars from tangent track, can lead to network-wide disruptions in service and ensuing delays. The Hatfield accident in Great Britain of 1993 provides evidence of this (Commission for Integrated Transport, 2002). The demand for high quality service at reasonable cost and with adequate protection from these various external forces has placed a heavy burden on the freight transport industry. There is increased pressure on this sector to balance these conflicting objectives of providing high service and security levels while simultaneously offering low cost transport alternatives.

A characteristic of a secure and highly functioning transport network, i.e. a resilient network, is its ability to recover from disruptions. This ability depends on the network structure and activities that can be undertaken to preserve or restore service in the event of a disaster or other disruption (For example, Chrysler used expedited truck service to backup air freight transport for transporting critical components from Virginia to Mexico immediately after September 11, 2001 (Martha and Subbakrishna, 2002)). In this chapter, an indicator of network resilience is defined that quantifies the ability of an intermodal freight transport network to withstand and quickly recover from a disruption. Recovery activities that might be taken in the immediate aftermath of a disruption, as well as the duration of time and investment required to undertake related actions, are considered *a priori*.

To quantify a network's level of resilience, a solution technique based on concepts of Benders decomposition, column generation and Monte Carlo simulation is proposed. In addition to quantifying the network's level of resilience, this technique determines an optimal course of action (i.e. set of activities) to undertake in the immediate aftermath of a disaster given target operational levels and a fixed budget. Research has been conducted on steps that can be taken to quickly restore system performance following a disaster (e.g. Daryl (1998), Williams et al. (2000), and Juhl (1993) consider recovery actions in the aftermath of tornados, tropical storms and bombings). Quick identification of the appropriate actions to take can play a crucial role in mitigating ensuing post-disaster economic and societal loss. For example, repair activities can be undertaken to restore critical infrastructure damaged in the disaster to pre-disaster conditions, traffic can be rerouted, equipment and personnel can be rescheduled, efficiencies in operations can be enhanced, and logistics providers can collaborate. That is, the performance of a network post-disaster depends not only on the inherent capability of the network to absorb externally induced changes, but also on the actions that can be taken in the immediate aftermath of the disaster to restore system performance. The resilience indicator can aid in pre-disruption network vulnerability assessment and making pre-disaster, vulnerability-reduction investment decisions.

In the next section, related studies on the measurement of network performance under uncertainty are described. Network resilience is defined and a stochastic, mixed integer program based on an intermodal freight network representation is presented for computing resilience in Section 4.3. In Section 4.4, Monte Carlo simulation is proposed for generating possible network states for given problem scenarios with dependencies. Benders decomposition is employed in the exact solution for a given network state. The network resilience definition, solution technique and resulting resilience levels, along with recovery activities, are illustrated on the Double-Stack Container Network (Morlok and Chang, 2004; Sun et al., 2006) under a variety of scenarios, including scenarios meant to replicate conditions under flooding, earthquake and terrorist attacks, in Section 4.5. Results from additional experiments designed to uncover the role network structure plays in resilience level are also presented. The last section summarizes the contributions of this work and discusses future potential extensions.

4.2 Related studies

Events that cause disruptions in nearly all human-made systems are often unpredictable, and, at some level, are inevitable. Thus, to prepare for such events, significant effort has been spent to predict system performance under disruption, identify critical functions and vulnerabilities, and develop means of reducing these vulnerabilities. Measures of network-level vulnerability have been employed widely across a host of arenas, including telecommunications, water and other critical lifelines. In this review of related studies, those works with greatest relevance are discussed.

A number of works consider vulnerability of transportation systems (see, for example, Taylor and D'Este (2003); Lleras-Echeverri and Sánchez-Silva (2001); Berdica

(2000)), where a sudden event may occur that reduces the performance of the network components or significantly impacts demand for use of services offered. Berdica (2002) defines vulnerability as susceptibility to disruptions that could cause considerable reductions in network service or the ability to use a particular network link or route at a given time. Networks that cannot quickly recover from a disruption with minimal reduction in service are deemed more vulnerable than those with quicker recovery time and lower overall experienced disruption. No method for the quantification of this measure is provided. Srinivasan (2002) discussed the potential of developing a quantitative framework for vulnerability assessment. Jenelius et al. (2006) argued that road network vulnerability is composed of the probability and consequences (represented by increased generalized travel cost) of single or multiple link failures. Although numerous attempts to measure vulnerability exist in the literature, vulnerability for transportation networks is still a rather ambiguous term, lacking a clear definition and methodology for its quantification.

Because vulnerability is often employed only qualitatively, quantitative measures of reliability have been used to gain insight into a system's level of vulnerability. Berdica (2002) argued that vulnerability is reliability in the road transportation system. Husdal (2004) linked vulnerability and reliability from a cost-benefit perspective, with vulnerability the cost and reliability the benefit value. Husdal argued that vulnerability is equivalent to "non-reliability" in certain circumstances. Dayanim (1991) argued that it was mandatory to incorporate reliability criteria into network design processes so as to meet disaster recovery requirements. A variety of reliability measures have been implemented for transportation systems to measure their intended functions under uncertainties. For example, connectivity reliability is defined as the probability that the network nodes remain connected (Iida, 1999). Travel time reliability is concerned with the probability that a trip can reach its destination within a given period (Bell and Iida, 1997)). Clark and Watling (2005) computed system-wide travel time reliability based on the probability distribution of network travel time under variable demand. Capacity reliability (Chen et al., 2002) is defined as the probability that the network can adapt to external changes while maintaining a given service level. Elefteriadou and Cui (2007) provided a review of a host of definitions of travel time reliability proposed in the literature.

Another relevant measure is flexibility. Goetz and Szyliowicz (1997) suggested that flexibility can be useful in coping with uncertainty. While primarily used in manufacturing systems analysis, several works have considered its application in assessing transportation systems. Feitelson and Salomon (2000) discussed flexibility from the infrastructure manager's perspective and define flexibility as the network's ability to adapt to changing circumstances and demands. Cost and ease of building additional network capacity are considered. Cho (2002) defined capacity flexibility as the ability of a traffic network to expand its capacity to accommodate changes in demand for its use while maintaining a satisfactory level of performance. Morlok and Chang (2004) extended this definition from the perspective of external changes in both travel demand (traffic volume and pattern) and network capacities. Sun et al. (2006) further measured flexibility in a more complicated problem setting, where future traffic patterns, service deterioration and stochastic demand are considered.

Diverse measures of resilience have been proposed for measuring the performance of engineering systems. For example, resilience is defined as the number of failures that a computer network can sustain to remain connected (Najjar and Gaudiot, 1990). For supply networks, resilience is described as the ability to cope with externalities and restore normal operations (Rice and Caniato, 2003). Konak and Bartolacci (2007) used traffic efficiency, defined as the expected percent of the total traffic that a network can manage, as a measure of resilience for telecommunication networks. McManus et al. (2007) define organizational resilience as a function of system-awareness, identification and management of the most critical system components, and adaptability. A measure of resilience is introduced by Murray-Tuite (2006) in the context of transportation. In her work, resilience is viewed as a network characteristic that indicates how well the traffic network performs under unusual circumstances. Resilience is seen as having ten dimensions (redundancy, diversity, efficiency, autonomous components, strength, collaboration, adaptability, mobility, safety, and the ability to recover quickly) which are individually computed based on results of simulation runs.

One can view the measures of reliability, flexibility and resilience as indicators of vulnerability. Such measures from prior works have wide interpretation, are often intertwined, and are sometimes interchangeable. Their definitions vary, although, the majority involve some element of risk, as they are defined based on a combination of the probability of the occurrence of the disruptive event, the negative impacts of the disruption, and aspects of network performance under disruption.

In this chapter, resilience is defined as a network's capability to resist and recover from a disruption or disaster. This definition reflects both the network's inherent ability to cope with disruptions by means of its topological and operational attributes and potential immediate actions that may be taken in the aftermath of the disruption that would otherwise not be considered. For example, a link may be constructed that did not exist in the original network. As recovery is the process of reconstructing, restoring, and reshaping the physical, social, economic, and natural environment through pre-disaster planning and post-disaster actions (Havidán et al., 2007), the proposed resilience measure considers both pre-disaster planning through consideration of the existing network topology and attributes and immediate post-disaster actions (i.e. potential recovery activities). Although numerous definitions of indicators of network performance exist in the literature, only qualitative measures of resilience related to business contingency planning exist that explicitly consider the impact of such post-disaster actions (Havidán et al., 2007). No prior work exists that provides the means of quantifying such a measure.

4.3 Definition and problem formulation

While the proposed definition of resilience and method for its quantification can be applied widely, the focus herein is on assessment of an intermodal freight transport system. Such systems involve multiple modes (truck, rail, and marine) in the movement of cargo between their origins and destinations. In this section, a definition of resilience for intermodal freight transport networks is introduced and a mathematical formulation that seeks an optimal set of recovery activities to undertake in the immediate aftermath of a disaster such that the network's resilience is maximized and budget constraints are met is proposed. Formulation and solution of this mathematical program relies on a multi-modal network representation described in this section.

4.3.1 The resilience indicator

Measurement of network resilience of an intermodal freight transport system should take into consideration the level of effort (cost, time, resources) required to return the network to normal functionality (or a fixed portion thereof, e.g. 90% functionality) or the impact of a given level of effort (in terms of cost, time, resources) on restoring the network to its original level or fraction thereof of functionality (ability to handle demand D by time T_0). Rose (2004) describes resilience as consisting of two components: inherent and adaptive. In this regard, the network resilience indicator defined herein consists of inherent network properties, e.g. redundancies, and a set of adaptive actions, i.e. recovery activities. With this in mind, network resilience, α, is defined in equation (1) as the post-disaster expected fraction of demand that, for a given network configuration, can be satisfied within specified recovery costs (budgetary, temporal and physical).

$$\alpha = E\left(\sum_{w\in\mathbf{W}} d_w / \sum_{w\in\mathbf{W}} D_w\right) = \frac{1}{\sum_{w\in\mathbf{W}} D_w} E\left(\sum_{w\in\mathbf{W}} d_w\right), \tag{1}$$

where d_w is the maximum demand that can be satisfied for origin-destination (O-D) pair w post-disaster and D_w is demand that can be satisfied for O-D pair w pre-disaster. This definition also recognizes that arc capacities depend on the characteristics of the disruption-causing event and, therefore, cannot be known *a priori* with certainty. Thus, if any network attribute that impacts its computation is random, as is the case with arc capacities, d_w is a random variable. The set of conceivable disaster events, each with stochastic outcomes in terms of network attributes, is considered in the computation of α.

4.3.2 Network representation

A network representation of the intermodal system is used, given by $G = (N, A)$, where $N = \{1,...,n\}$ is the set of nodes, $A = \{(i, j) | i, j \in N\}$ is the set of directed arcs. G consists of sub-networks, one for each mode. One can view each sub-network on a plane, where transfers between modes take place along transfer arcs connecting designated nodes (representing intermodal terminals) of the various planes, as shown in Figure 4-1. The transfer arcs are represented as vertical arcs in the figure.

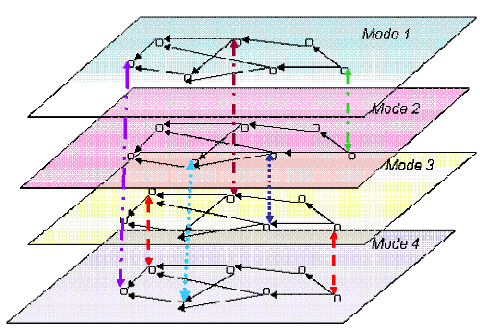


Figure 4-1 Intermodal network representation (Zhang et al., 2008)

Each modal or transfer arc $a \in A$ has associated with it a positive capacity, denoted by c_a, with integral domain and range, and a positive traversal (or transfer) time τ_a. The capacity of each modal arc represents the number of shipments that can be transported along the arc and the capacity of each transfer arc represents the number of shipments that an intermodal terminal can handle. Note that because the type and timing of the event and its impact cannot be known *a priori* with certainty, c_a and τ_a are random variables.

A set of O-D pairs, W, is also given. Each O-D pair $w \in W$ has an origin $r(w)$, a destination $s(w)$, and a given demand, i.e. number of shipments, D_w to be shipped between its origin and destination. A path is defined as an acyclic chain of arcs. A shipment can only be transported along a path with the same origin and destination as the shipment. Let P_w be the index set of all paths that start from $r(w)$ and end at $s(w)$. The time for traversing path $p_w \in P_w$ is computed from the sum of traversal times of its constituent arcs.

Additional notations employed in the mathematical formulation of the network resilience problem are defined as follows.

$\mathcal{K}$ = the set of candidate recovery activities, $\mathcal{K} = \{k = 1,2,...,K\}$

Δc_{ak} = change in capacity of link *a* if recovery activity *k* is implemented

t_{ak} = travel time of link *a* could be reached if recovery activity *k* is implemented

q_{ak} = time needed to implement recovery activity *k* on link *a*

Q_p^R = maximum implementation time of recovery activities taken along path p

$T_w^{\max}$ = maximum allowable travel time for O-D pair w

b_{ak} = cost of implementing recovery activity k on arc a

B = maximum allowable cost of recovery activities

δ_{ap} = in path-link incidence matrix; δ_{ap}=1, if path p uses link a and δ_{ap}=0, otherwise

Decision variables:

f_p = number of shipments transported on path p

y_p = binary variables indicating whether or not shipments use path p

$\bar{d}_w$ = number of shipments that cannot be satisfied for O-D pair w

γ_{ak} = binary variables indicating whether or not recovery activity k is undertaken on arc a

4.3.3 Problem formulation

The network resilience problem can be formulated as a stochastic, mixed integer program shown in (P): (2) – (11), where ω is a given realization of random arc capacities $\tilde{\omega}$. Any realization of all $\tilde{\omega}$ is referred to as a network state. Program (P) contains integer variables, representing the selection of recovery activities on corresponding arcs and the selection of paths carrying flow, and continuous variables, representing the flow along each path and demand that cannot be satisfied for each O-D pair.

$$(P) \quad E_{\tilde{\omega}}\left[\min \sum_{w\in W} \bar{d}_w(\omega)\right] \tag{2}$$

$$s.t. \qquad \sum_{p\in P_w} f_p(\omega) = D_w - \bar{d}_w(\omega) \quad \forall w \in W, \tag{3}$$

$$\sum_{w \in W} \sum_{p \in P_W} \delta_{ap} f_p(\omega) - c_a(\omega) - \sum_k \Delta c_{ak} \gamma_{ak}(\omega) \le 0 \quad \forall a \in A, \tag{4}$$

$$\sum_{a \in P} \tau_a(\omega) + \sum_{a \in P} \sum_k (t_{ak}(\omega) - \tau_a(\omega)) \gamma_{ak}(\omega) + Q_p^R(\omega) \le T_w^{\max}(\omega) + M(1 - y_p(\omega)), \quad \forall p \in P_w, w \in W \tag{5}$$

$$f_p(\omega) \le D_w y_p(\omega) \quad \forall p \in P_w, w \in W, \tag{6}$$

$$Q_p^R(\omega) - q_{ak} \gamma_{ak}(\omega) \ge 0 \quad \forall a \in p, k \in K, \tag{7}$$

$$\sum_a \sum_k b_{ak} \gamma_{ak}(\omega) \le B, \tag{8}$$

$$\sum_k \gamma_{ak}(\omega) \le 1 \quad \forall a \in A, \tag{9}$$

$$f_p(\omega), \bar{d}_w(\omega) \ge 0 \quad \forall p \in P_w, w \in W, \tag{10}$$

$$\gamma_{ak}(\omega), y_p \in \{0,1\} \quad \forall a \in A, k \in K, p \in P_w, w \in W. \tag{11}$$

The objective (2) of program (P) seeks to minimize the expected portion of demand that cannot be accommodated, i.e. it maximizes the expected number of shipments that can be sent from their origins to their destinations. To compute this expectation, $\sum_{w \in W} \bar{d}_w$ is evaluated over all possible realizations of random arc attributes.

Constraints (3) are flow conservation constraints. Constraints (4) are capacity constraints, restricting flow on each arc to be less than the capacity resulting from the impact of the event and recovery actions that are taken. Constraints (5) and (6) are level of service (LOS) constraints requiring that the time each shipment spends traversing a path $p \in P_w$ not exceed a given maximum duration $T_w^{\max}(\omega)$ and specific circumstances (i.e. network state ω). M is a sufficiently large positive constant. The time for traversing each path $p \in P_w$ is composed of three parts: constituent link travel times under post-disaster conditions, the maximum time required to implement recovery activities along constituent links (defined by Constraints (7)), and reductions in link travel times due to recovery actions. It is assumed that all recovery activities begin simultaneously, immediately after the event and any link chosen to undergo a recovery action will be out of service during the action's implementation. Constraints (5) and (6) provide a linear implementation of the equivalent complementarity constraint: $f_p\left(\sum_{a\in P}\tau_a+\sum_{a\in P}\sum_k\left(t_{ak}-\tau_a\right)\gamma_{ak}+Q_p^R-T_w^{\max}\right)\leq 0.$ Constraint (8) requires that the total cost of the selected recovery actions does not exceed a given budget. Constraints (9) require that only one recovery activity, representing a set of recovery actions, can be selected for each arc. This ensures that conflicting actions will not be simultaneously chosen. Non-negativity and integrality restrictions are given in constraints (10)-(11). Constraints (3)-(11) are evaluated for a given network state ω.

It is assumed that the revenue (including future revenue) from completing shipment deliveries in a timely manner in post-disaster circumstances significantly outweighs any savings that might be achieved in selecting optimal paths based on operational costs, and therefore, operational costs are not included in the model. If desired, an additional set of constraints with similar form as constraints (5) can be incorporated in the formulation to limit total operating expenses. This will increase the complexity of the problem, but can be solved with the same solution technique.

While the formulation does not include pre-event decision variables, a network's resilience level under a given network state and set of potential remedial actions (if any) can be quantified by employing the formulation under one or more chosen scenarios pre-event. Remedial actions that may be taken pre-event include, for example: adding additional links to the network; ordering spare parts or backup equipment; prepositioning resources in anticipation of potential recovery activities; implementation of advanced technologies; training; and other pre-event actions that can reduce the time required to complete potential recovery activities should they be required post-event. Such pre-event use of the formulation facilitates network vulnerability assessment and further informs the decision-maker in taking pre-event action to improve network resilience.

One will note that program (*P*) includes no first-stage variables. All decisions are taken once the outcome of the random disaster event is known. Thus, the problem can be directly decomposed into a set of independent scenario-specific deterministic problems and the focus of the solution approach presented in the succeeding section is on the sampling methodology and exact solution of each independent deterministic problem that results for a given realization of the capacity random variables (i.e. a network state). Denote the deterministic problem for a given network state by problem (*DP*). Proof that the recognition version of problem (*DP*) is NP-complete is given in Proposition 1. It follows that problem (*DP*) is NP-hard.

Proposition 1. The recognition version of problem (*DP*) is NP-complete.

Proof. To prove that the recognition version of problem (*DP*) is NP-complete, a transformation from the recognition version of the knapsack problem, a well-known NP-complete problem (Garey and Johnson, 1979), to the recognition version of problem

(DP) is constructed.

An instance of the recognition version of the knapsack problem is given by a finite set $I = \{i_1, i_2, ..., i_n\}$ of items, each with a nonnegative weight w_i and value v_i. The problem is to determine if there exists a subset of items $I' \subset I$ with total weight $w(I') \le W$ and total value $v(I') \ge V$.

Assume that $T_w^{\max}$ is set sufficiently large so that LOS constraints (5) will not be binding. Construct a network G with only one O-D pair (s, t) connected by n parallel arcs. Each arc has a capacity c_a. Suppose only one recovery activity is available for each arc and will increase the arc capacity by v_a with an implementation cost w_a, a fraction of the budget W. Then, each arc a in G can be transformed into two parallel arcs a_1 with capacity c_a and cost 0, and a_2 with a capacity v_a and cost w_a. Thus, the instance of the knapsack problem has a solution if and only if there is a flow that sends at least $V + \sum_a c_a$ shipments from s to t with a cost of at most W. This transformation can be achieved in polynomial time. This, together with the fact that the recognition version of problem (DP) is in NP, proves that problem (DP) is NP-complete. ♦

4.4 Solution technique

To measure network resilience for a given network topology and associated operating characteristics, as well as a given set of potential recovery activity options, problem (DP) can be solved directly; however, this may require extraordinary effort. The number of variables is large, even for mid-size instances. Thus, a framework employing Benders decomposition, column generation and Monte Carlo simulation is proposed that considers a manageable number of network states. For a given scenario (i.e. event), the joint probability distribution of the random arc capacities is assumed to be known. For each scenario considered, Monte Carlo simulation is used to generate the values of random arc capacities required to specify the set of possible network states, while preserving distribution properties (Subsection 4.4.2). A Benders decomposition technique that employs column generation in the solution of a set of sub-problems is developed to find the maximum demand that can be satisfied for the given network state. Network resilience is computed from the expected value of the weighted sum of the maximum level of satisfied demand achieved for each replication as in equation (1). The solution technique is discussed in detail next.

4.4.1 Solving problem (DP)

4.4.1.1 Benders decomposition

Benders decomposition (Benders, 1962) is performed on program (*DP*), a mixed integer program over binary variables γ_{ak} and y_p. The original problem is reformulated into a sub-problem containing the continuous path flow variables and a master problem containing the binary recovery activity selection variables and path selection variables. Benders cuts are generated by solution of the sub-problem and are added to the relaxed master problem at each iteration, progressively constraining the relaxed master problem. The cuts reduce the number of flow variables that must be considered, even at the expense of increasing the number of constraints.

For simplicity, program (DP) can be transformed into a network flow problem with a single source and single sink by adding a super source r connecting to each source node $r(w)$ with capacity D_w and travel time $\left(T^{\max} - T_w^{\max}\right)$, where $T^{\max}$ is the maximum allowable travel time for any r-s path with positive flow, and a super sink s connected to each sink node $s(w)$ by arcs with capacity $\sum_{w \in W} D_w$ and zero travel time. Denote the path set between r and s by P. The exact algorithm presented hereafter is applied in solving this r-s network flow problem.

Let γ be a 0-1 vector satisfying constraints (8) and (9), and let Λ be the set of valid γ. For given $\hat{\gamma} \in \Lambda$, the primal sub-problem can be stated as follows.

$$SP(\hat{\gamma}): \quad \max \sum_p f_p \tag{12}$$

$$s.t. \quad \sum_{p \in P} \delta_{ap} f_p \le c_a + \sum_k \Delta c_{ak} \hat{\gamma}_{ak} \quad \forall a \in A, \tag{13}$$

$$\sum_{a \in P} \tau_a + \sum_{a \in P} \sum_k \left(t_{ak} - \tau_a\right) \hat{\gamma}_{ak} + \max_{a \in p} q_{ak} \hat{\gamma}_{ak} \le T^{\max} + M\left(1 - y_p\right) \quad \forall p \in P, \tag{14}$$

$$f_p \le D y_p \quad \forall p \in P, \tag{15}$$

$$f_p \ge 0, y_p = \{0,1\} \quad \forall p \in P. \tag{16}$$

Problem $SP(\hat{\gamma})$ is a path-flow based formulation of a maximum flow problem with side constraints.

For a given $\hat{\gamma}$, the path set P can be separated into two disjoint subsets: $P_1 = \left\{ p \middle| \sum_{a \in P} \tau_a + \sum_{a \in P} \sum_k \left(t_{ak} - \tau_a\right) \hat{\gamma}_{ak} + \max_{a \in p} q_{ak} \hat{\gamma}_{ak} \le T^{\max}, \forall p \in P \right\}$, the set of paths between r

and s that satisfy LOS constraints, and

$$P_2 = \left\{ p \middle| \sum_{a \in P} \tau_a + \sum_{a \in P} \sum_k (t_{ak} - \tau_a) \hat{\gamma}_{ak} + \max_{a \in p} q_{ak} \hat{\gamma}_{ak} > T^{\max}, \forall p \in P \right\},$$

the set of paths between r and s that do not satisfy LOS constraints. By considering only P_1, sub-problem $SP(\hat{\gamma})$ can be reformulated with only continuous decision variables given by sub-problem $LSP(\hat{\gamma})$:

$$LSP(\hat{\gamma}): \quad \max \quad \sum_p f_p \tag{17}$$

$$s.t. \quad \sum_{a \in p / p \in P_1} f_p \leq c_a + \sum_k \Delta c_{ak} \hat{\gamma}_{ak} \quad \forall a \in A, \tag{18}$$

$$f_p \geq 0, \quad \forall p \in P_1. \tag{19}$$

The dual sub-problem is given as follows.

$$DSP(\hat{\gamma}): \quad \min \quad \sum_{a \in A} \left(c_a + \sum_k \Delta c_{ak} \hat{\gamma}_{ak} \right) \pi_a \tag{20}$$

$$s.t. \quad \sum_{a \in p} \pi_a \geq 1 \quad \forall p \in P_1, \tag{21}$$

$$\pi_a \geq 0 \quad \forall a \in A. \tag{22}$$

where π_a are the dual variables associated with constraints (18). The primal sub-problem $LSP(\hat{\gamma})$ is always feasible, because 0 is always a feasible solution, and a feasible solution for $DSP(\hat{\gamma})$ can be readily obtained. Thus, by the weak duality theorem, the primal and dual sub-problems are bounded.

The Benders master problem is obtained by replacing constraints (4) - (7) by Benders cuts (24). Constraints (24) are optimality cuts that ensure that affected non-optimal solutions are excluded. Let D denote the polyhedron defined by constraints

(21) and P_D be the set of extreme points of *D*. Introducing the additional free variable *Z*, program (*DP*) can be reformulated as the following equivalent problem MP.

$$MP: \quad \max \quad Z \tag{23}$$

$$s.t. \qquad Z - \sum_{a \in A} \sum_{k \in K} \Delta c_{ak} \pi_a \gamma_{ak} \leq \sum_{a \in A} c_a \pi_a, \ \forall \pi \in P_D \tag{24}$$

(8), (9), (11)

Constraints (24) need not be exhaustively enumerated, because most of the constraints will be inactive in the optimal solution. Thus, a relaxation of problem (*MP*), denoted as (*RMP*), can be obtained by dropping constraints (24) and iteratively adding them to the relaxation until optimality is achieved.

To improve (*RMP*), constraints (8) can be replaced by (8'):

$$B - \sigma < \sum_a \sum_k b_{ak} \gamma_{ak}(\omega) \leq B, \tag{8'}$$

where σ is the maximum implementation cost over all recovery activities. One can show that constraints (8') are more restrictive than (8) for problem (*RMP*), thus, creating a smaller feasible region. Moreover, the optimal solution will not be cut off by this inequality. This can be shown by considering the following. Suppose an optimal solution (γ^*, y^*, f^*) to program (*P*) with objective function value z^* exists such that $B - \sum_a \sum_k b_{ak} \gamma_{ak}^*(\omega) \geq \sigma$, then there exists at least one arc a for which $b_{ak} \leq \sigma$ and $\sum_k \gamma_{ak}^* = 0$. The corresponding recovery activity with cost $b_{ak} \leq \sigma$ can be undertaken without violating constraints (3)-(11). The resulting solution is a feasible solution with objective function value no greater than z^*.

4.4.1.2 Column generation for sub-problem solution

Primal and dual sub-problems are solved by iteratively generating Benders optimality cuts that constrain problem (*RMP*). Both sub-problems $LSP(\hat{\gamma})$ and $DSP(\hat{\gamma})$ are path-flow based formulations. The number of path-flow variables grows exponentially with the size of the network, making both problems difficult to solve. Thus, a column generation-based technique (see Wolsey (1998) for general background) is applied that narrows in on a limited set of paths. The column generation algorithm presented in this section is an iterative method, which takes advantage of sub-problem $LSP(\hat{\gamma})$'s structure and constructs a series of sub-problems, each increasingly more restricted. At each step, new paths (i.e. columns) are generated, expanding the restricted subset of P_1, defined in the previous subsection. The algorithm terminates when no new path (i.e. column) can be identified for inclusion in this subset.

The column generation process starts with an initial subset of path variables. The reduced cost of f_p is computed as $\bar{c}_p = 1 - \sum_{a \in p} \pi_a$. The optimality condition is given by $\bar{c}_p \le 0, \forall p \in P_1$. If there exists a path $p \in P_1$ such that $\bar{c}_p > 0$, then f_p should be chosen as the variable that enters the limited path set. The new column will be identified by considering which constraints in the dual sub-problem are most violated. If the constant 1 is ignored in computing reduced costs, the problem of choosing the entering column is a shortest path problem with a path traversal time constraint. A variety of algorithms have been proposed in the literature to address this problem (e.g. Aneja et al., 1983; Handler and Zang, 1980; Desrosiers et al., 1995). In implementations described in section 4.5, a label-setting algorithm based on concepts of dynamic programming concepts that can be attributed to Dumitrescu and Boland (2003) is used.

4.4.1.3 Upper and lower bounding

The Benders relaxed master problem (*RMP*) becomes increasingly constrained as Benders cuts are added, providing an upper bound on the objective value of the original problem that is non-increasing with every iteration. Moreover, a feasible solution is obtained, generating a lower bound, and possibly improving the best lower bound, at each iteration. The algorithm stops when upper and lower bounds meet. Thus, tight bounds are important to accelerating the convergence of the algorithm.

An initial upper bound on problem (*RMP*) is obtained by relaxing binary variables $\gamma_{ak}\ \forall a,k$ in problem (*DP*) and solving the corresponding relaxed problem, a constrained optimal capacity expansion problem with linear cost functions. If path constraints are relaxed, the capacity expansion problem can be solved in polynomial time. Thus, a similar technique as used to solve the Benders sub-problem, sub-problem $LSP(\hat{\gamma})$, is applied to solve this relaxed problem and generate the initial upper bound.

To generate an initial feasible solution, and an initial lower bound, to problem (*RMP*), the following lexicographic ordering rules can be applied, where γ_{ak} is obtained during the process of determining an initial upper bound on problem (*RMP*): 1) rank all the γ_{ak} variables by their values, giving priority to those with the largest capacity when ties exist and 2) obtain a limited set of γ_{ak} variables from the order produced in (1) with the maximal value of $\sum_{a,k} b_{ak}$ such that $\sum_{a,k} b_{ak} \le B$ and set $\gamma_{ak} = 1$ for all variables in the set.

The lower bound does not follow an increasing trend, because the objective function value obtained from consecutive iterations may vary significantly. To address this issue, local branching proposed by Fischetti and Lodi (2003) is applied to identify a feasible solution that results in an improved lower bound. Rei et al. (2009) discussed the possibility of using local branching to increase the speed of Benders decomposition. Their idea is to seek an improved feasible solution (and improved lower bound) by considering a small sub-region of the feasible space surrounding the previously identified feasible solution. Given feasible solution $\{\tilde{\gamma}_{ak}\}_{a,k}$ of problem (*RMP*) and a positive integer parameter *k*, the local branching constraint can be written as:

$$\Delta(\gamma, \tilde{\gamma}) = \sum_{\tilde{\gamma}_{ak}=1} (1 - \gamma_{ak}) + \sum_{\tilde{\gamma}_{ak}=0} \gamma_{ak} \le k \ . \tag{25}$$

The local branching constraint divides the feasible region into two branches. Branching strategies are used continuously to generate better solutions until no improved solution can be found or a prescribed computational time limit is reached. Through local branching, multiple Benders cuts can be generated at each iteration.

4.4.1.4 Benders decomposition algorithm

Details of the Benders decomposition algorithm built on concepts described in previous subsections and proposed for solution of problem (*DP*) are described next.

1. Set $t := 1$ and $P_D^1 := \varnothing$. Solve the relaxation of problem (*DP*) (γ is relaxed) to generate an upper bound, UB. Generate a feasible solution according to lexicographic ordering rules.

2. Solve the Benders master problem and sub-problems.

   2.1. Solve problem (RMP^t). Let γ^t be an optimal solution of objective function value Z^t. $UB = \min\{UB, Z^t\}$. Use local branching to identify feasible solutions.

   2.2. Solve sub-problem $LSP(\hat{\gamma}^t)$ via column generation.

      2.2.1. Let the initial column be given by the shortest *r-s* path. If the LOS constraint is not satisfied for the shortest path, stop.

      2.2.2 Construct the restricted master problem using identified paths (i.e. columns) and solve to generate dual prices.

      2.2.3 Use the dual prices obtained in Step 2.2.2 to solve the constrained shortest path problem. If $\bar{c}_p \leq 0, \forall p \in P_1$, stop; otherwise, identify columns (i.e. paths) for which $\bar{c}_p > 0$, add the new column to the master problem, and return to step 2.2.2.

3. Let $\{f_p^t\}$ be a primal optimal solution and z^t be the sub-problem objective function value. Lower bound, $LB = \max\{LB, z^t\}$. If $UB = LB$, then (γ^t, f_p^t) is an optimal solution to problem (*DP*), stop; otherwise, set $P_D^{t+1} = P_D^t \cup (\gamma^t, f_p^t)$ and $t = t+1$. Return to step 2.

The algorithm terminates with an optimal solution to problem (*DP*).

4.4.2 Monte Carlo simulation

In the previous subsection, an exact Benders decomposition technique is proposed for solution of problem (*DP*), the deterministic equivalent problem of stochastic program (*P*). To compute network resilience, Monte Carlo simulation is employed to generate a manageable number of samples (each sample creates an instance of problem (*DP*)) from random variates defined on the probability space to approximate the expectation of equation (1). This idea of sample average approximation has been suggested by numerous authors (e.g. Shapiro and Philpott, 2007).

Monte Carlo methods are widely used to simulate the random behavior of systems through repeated sampling from random variables with given probability distributions. In an intermodal transport network, dependency among random arc capacities can be expected. For example, an earthquake will impact all transportation facilities in the same area at the same time. Correlation in arc capacity among these adjacent facilities should be expected and the correlation structure will differ considerably for varying types of events. To preserve the specified correlation structure among the random variables associated with the given event, the employed Monte Carlo method must generate random variates that maintain the same probabilistic characteristics. The approach developed by Chang et al. (1994) is applied to generate multivariate correlated random variates of arc capacities (see Appendix A for additional detail). This method has been previously applied in the context of transportation systems to generate random interdependent link capacities (Chen et al., 2002). After a realization of the random parameters is generated, the exact method proposed in the previous subsection can be applied to solve each program (*DP*) for the given realization. The individual objective function values are collected to compute the resilience indicator α.

4.5 Numerical experiments

In this section, results of two sets of numerical experiments are presented. The first set of experiments involved an intermodal freight network in the Western U.S. These experiments were designed to illustrate the resilience concept proposed herein. The second set of experiments was conducted on four carefully designed hypothetical networks to study the role a network's structure plays in resilience. The proposed solution technique described in Section 4.4 was implemented in Microsoft Visual Studio C++ 6.0 language with the ILOG CPLEX callable library 9.1 (2005). Experiments were run on a personal computer with Pentium (4) CPU 3.20 GHz and 2.00 GB of RAM.

4.5.1 Illustration on Double-Stack Container Network

The solution technique is applied to the 8-node, 12-arc Double-Stack Container Network as depicted in Figure 4-2. This rail network covers a wide area in the Western U.S. It involves 17 potential O-D pairs and includes nodes representing such cities as Chicago, Los Angeles, and Houston. In double-stack operations, containers are stacked one on top of another in layers of two. Additional detail concerning the network topology can be found in (Morlok and Chang, 2004; Sun et al., 2006). Container travel times, including travel time along arcs and handling in railway terminals, are defined for each O-D pair. While not depicted in Figure 4-2, intermodal connections exist at every node (i.e. city) in the network, connecting the rail terminals with the highway network. A virtual highway link between every O-D pair was employed to model highway operations. Their travel times were set using estimates from GoogleMap and capacity was assumed to be sufficient to handle all freight transport demand for the region.

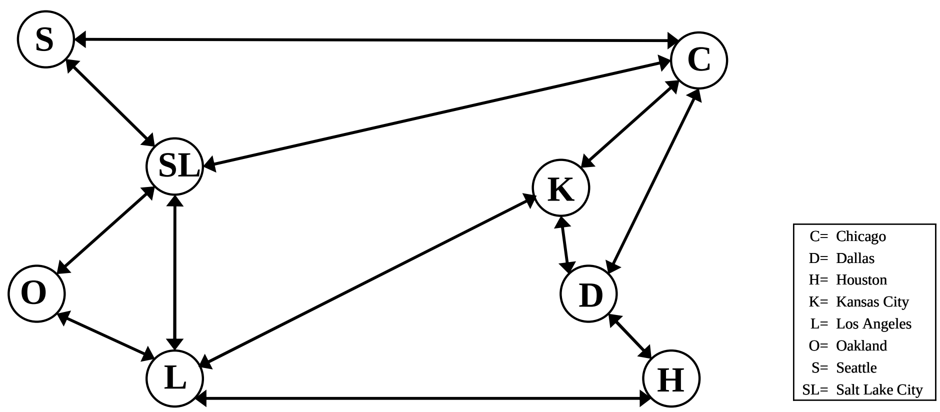


Figure 4-2 Western U.S. Double-Stack Container Network.

Five types of scenarios were considered in these experiments as described in Table 4-1. Factors considered in the construction of these scenarios include the disaster classification, consequences of the disaster in terms of impact on arc capacities and intermodal operations, and an appropriate correlation matrix for the given disaster classification. In all scenarios considered, it was assumed, for simplicity, that only rail links were impacted or can be addressed through recovery activities.

Table 4-1 Characteristics of test scenarios

Scenario	Description	Details on arc dependencies
1	Bombing	Randomly selected links in the network are nonfunctioning
2	Terrorist attack	Negative impact on arc capacities, large negative impact close to the emergency scene, less impact away from the emergency scene
3	Flood	Multiple connected links nonfunctioning over a large area
4	Earthquake	Randomly selected links over a large area are negatively impacted
5	Intermodal terminal attack	Flow into and out of terminals in Chicago and Los Angeles significantly impacted due to an attack

For area-wide disasters, as might arise under scenarios involving an earthquake (i.e. scenario 4), highway links may suffer similar disruption as rail links in affected subregions. For simplicity, in the experiments the duration required to traverse the highway links where a terminal exists in an affected subregion is increased by 30% from the average to account for likely delays incurred along the highway links. Greater increases might be considered, where devastation due to the disaster event is found to be very significant, and more detailed modeling of traffic impacts can be employed for greater accuracy.

Dependencies among capacity random variables, which specify each scenario, are a function of the disaster classification. For instance, a snow storm will simultaneously affect all network components in the same area, leading to strong correlation among arc capacity random variables of adjacent arcs. And a terrorist attack on some location within the network will cause serious damage to one or more network components in a small area. Monte Carlo simulation is used to generate the realization of interdependent arc capacities (specifying a network state) for a given scenario. Different correlation matrices are applied for each distinct scenario. In this chapter, the arc capacity, $c_a, \forall a \in A$, is assumed to be a uniform random variable with a specified range $[l_a, u_a]$.

Several recovery activities, defined as activities that can be taken in the immediate aftermath of a disaster to mitigate the disaster's negative impacts and restore network capacity, are considered for implementation. Examples of potential recovery activities include, among others, rerouting shipments employing alternative transport modes (e.g. from rail to truck); restoring and repairing damaged infrastructure; building temporary roadways; instituting access control to an impacted area; utilizing spare parts or equipment, as well as extra personnel; and employing advanced traffic management strategies. Six hypothetical recovery activities were considered in the experiments, each with different duration, cost and effect as delineated in Table 4-2. While the recovery actions are generically defined, these actions are consistent with activities that might be undertaken to mitigate the impact of the specific disasters considered in scenarios 1 through 5. For example, the changes created through recovery activity 2 are consistent with high-cost, short duration construction actions associated with capacity restoration along links of the network. Improvements rendered through recovery activity 3 may be consistent with the use of spare equipment, thus, the low cost, but relatively moderate impact.

Intermodal networks may be more vulnerable than single-mode networks in terms of exposure to risk, but intermodal options provide greater opportunity for recovery in the immediate aftermath of disaster. Recovery option 6 was designed to illustrate the impact of recovery opportunities that exist by virtue of intermodal connections, though needed as a consequence of an attack on intermodal terminals or other network link (scenario 5). An attack on an intermodal terminal would impact the ability to process intermodal containers. To accommodate affected shipments, containers that were to be shipped within the rail network through the impacted terminal can be rerouted along alternative railway lines or might be handled through truck transport along the highway links. Changes in arc capacity, implementation duration and costs resulting from and required for implementation of recovery activity 6 are consistent with a mode shift from rail to truck as might be required in response to a scenario like scenario 5. The high cost of transfer is expected due to the cost of terminal operations and the additional expenses associated with the last-minute hiring of trucking companies for what might be considered emergency circumstances. This last recovery activity assumes that capacity for transfer to truck is sufficient to meet all new demand. Alternate recovery actions might be considered under scenarios in which this is not the case.

Assumptions regarding the durations and costs of recovery activities are given in Table 4-2. For each railway arc, it was assumed that pre-event arc travel times and capacities are known. Post-event capacities are randomly generated in accordance with the characteristics of the event and changes in travel times resulting from reduced capacity are determined as a function of change in capacity. Any change in arc travel time that results from a recovery activity is assumed to be directly correlated with improvements in arc capacity resulting from that activity. For example, under the first scenario, if a recovery activity results in x percent increase in capacity along an arc, it is assumed that the arc travel time decreases by $0.1x$ percent. The total budget is assumed to be 30 units and travel time limitations are set for individual O-D pairs to a value slightly larger than the time required by the shortest path.

Table 4-2 Characteristics of recovery activities

Recovery activities	Recovery activity duration (units)	Cost (units)	Recovery activity effect (% increase in affected capacity)	Applicable for arcs
1	2	6	10	1-12
2	1	10	10	1-6
3	6	1	5	7-12
4	4	4	10	1,3,5,7,9,11
5	3	8	15	2,4,6,8,10,12
6	3	10	Return to original capacity	1-12

To determine an appropriate sampling size for the Monte Carlo technique, 10,000 iterations were run for a test case from which the objective function value was collected for each iteration. It is noted that the average objective function value steadily increases in the early iterations of the simulation and was determined to stabilize after approximately 5,000 iterations. Thus, a stopping criterion of 5,000 iterations was employed in all remaining tests. One might alternatively consider the mean square error and maximum error differences in the resilience distribution in determining an appropriate iteration in which to terminate the procedure.

Computational results of the experiments are given in Figure 4-3. To compare the impact of recovery activities on resilience level under varying scenarios, post-event resilience is measured assuming that post-event conditions will remain if no recovery activity is taken. Note that the resilience indicator proposed herein was designed for pre-event analyses. Thus, one could compute resilience of the Double-Stack Container Network as defined in prior sections, where all potential scenarios are considered in the computation.

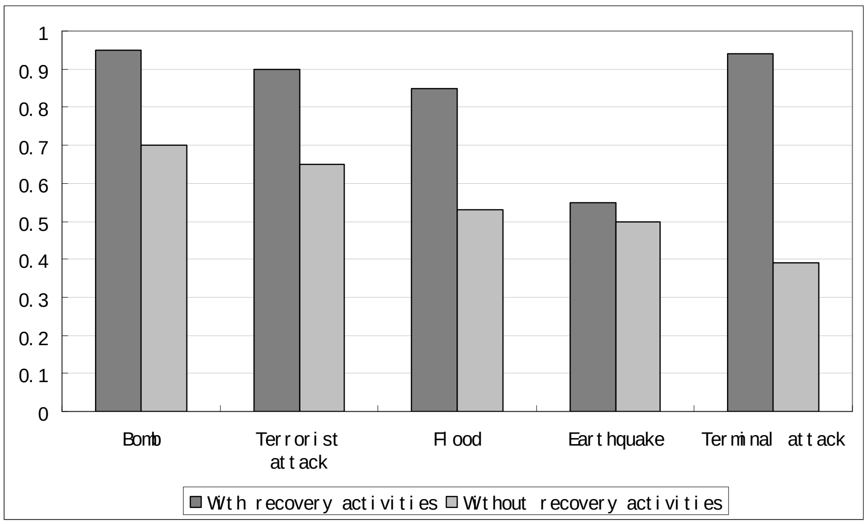


Figure 4-3 Computational results for different scenarios

The results show that recovery activities can lead to significant improvement in resilience level, indicating the importance of recovery activities in terms of network performance in the aftermath of a disaster. Over all tested scenarios, an average improvement in resilience of approximately 57% (with a range of 10 to 141%) was found as a consequence of considering recovery activities. It is worth noting that the resilience level is much smaller for scenario 4, where an earthquake is presumed to have occurred, than for other scenarios. This is due both to the greater link capacity degradation experienced in the scenario and presumed effectiveness of recovery activities. For example, in an earthquake, it is presumed that the impact of the disaster event on both rail and highway is similarly significant. The wide difference between resilience levels with and without recovery activity options associated with scenario 5, involving attacks on intermodal terminals in Chicago and Los Angeles (perhaps the busiest terminals in the network), illustrates the magnitude of the potential role of recovery activities on system performance.

To further illustrate the proposed concept of resilience, intermodal network implementations of network reliability and flexibility as defined in (Chen et al., 1999; Chen et al., 2002; Morlok and Chang, 2004; Sun et al., 2006) are computed under each scenario for the illustrative rail network and are compared with resilience. Chen et al. (1999 and 2002) define reliability as the probability that the network can accommodate the demand while maintaining a given service level and Morlok and Chang (2004) (also adopted in Sun et al., 2006) define flexibility as the ability to efficiently utilize the capacity of a traffic network to accommodate variations in demand while maintaining a satisfactory LOS.

To compute these measures of reliability and flexibility, a bi-level optimization model was constructed in which lower-level decisions involve the assignment of traffic to the network and upper-level decisions involve the determination of the maximum demand multiplier (referred to as the reserve capacity) permissible given problem constraints. Similar constraints employed to measure resilience are employed in these models. Reliability is equal to the probability that the maximum multiplier can be set to a value greater than the base demand level given random link capacities. Flexibility, on the other hand, is set to the difference between the maximum multiplier and base demand level divided by the base demand level. In Morlok and Chang's work on flexibility, capacities are assumed to be fixed. Here, the expected value was determined.

While, like resilience, reliability and flexibility are typically measured with no knowledge of a particular disaster event, to illustrate the impact of recovery activities on these network performance measures, post-event values are computed. The values of post-event reliability and resilience (considered with and without recovery activities) obtained from the experimental results are recorded in Table 4-3. While post-event flexibility was computed, the values were very similar to those obtained for reliability and, thus, are omitted.

Table 4-3 Comparison by performance metric

Scenario	Post-Event Reliability	Post-Event Resilience	
		Without recovery activities	With recovery activities
1	0.65	0.7	0.95
2	0.6	0.65	0.90
3	0.51	0.53	0.85
4	0.48	0.5	0.55
5	0.39	0.39	0.94

The values of the network performance metrics given in Table 4-3 indicate that the measure of resilience when no recovery activities are considered provides similar information to its reliability and flexibility counterparts in all scenarios. When effective recovery activities are available, the reliability measure does not adequately capture a network's resilience level. For example, to mitigate the impact of a disaster caused by a bombing or terrorist attack (scenarios 1, 2 and 5), where highway links are relatively unaffected by the incident, shipments can be shifted from rail to truck. In such circumstances, a network's reliability may be quite low, but its resilience may be quite high. That is, resilient networks are not necessarily reliable. The cost of making a network highly reliable may be much greater than making it highly resilient, because resilience accounts for actions that can be taken in the aftermath of disaster once the disaster's impact is known. To achieve greater reliability, on the other hand, *a priori* actions must be considered to address all plausible disaster events. Thus, intermodal freight networks, as with other transportation networks, should be designed to meet acceptable levels of both reliability and resilience.

One can construct networks and circumstances for which there is even greater disparity in relative performance (as measured by reliability, flexibility and resilience) over the various scenarios. For example, it is possible that the resilience of a network under scenario A could be higher than for the network under scenario B, but the reliability of the network under scenario B is higher than it is under scenario A. This may arise, for example, where effective recovery activities under scenario B require greater investment than the budget allows.

4.5.2 Role of network structure in resilience level

Casey (2005) found that topologies of infrastructure sensor networks have a great impact on the networks' vulnerabilities to disruptions. In this section, additional experiments were developed to gain insight into the role of a network's topology in its resilience level given the possibility of disaster occurrence. Network structure and operating characteristics were carefully designed for this purpose. Arcs were treated generically to maintain a maximum level of consistency in all experiments so as to isolate network structure from other features that could impact resilience level. Four network structures were considered: a complete network, where each node pair is connected by two oriented directed arcs with opposite direction; a random network with average degree two and indegree (and outdegree) of each node ranging between one and three; a grid network with a regular grid structure; and a network with multiple hubs, i.e. with three completely connected hubs into which traffic from outlying nodes feed. All networks were created with symmetry, i.e. if an arc originates from node *i* that is incident on node *j*, another arc originates at node *j* that is incident on node *i*.

Table 4-4 Network structures

Networks	# of nodes	# of arcs	Average indegree
Complete network	10	90	9
Random network	10	20	2
Grid network	10	30	3
Hub-based network	10	30	3

Table 4-4 synopsizes the characteristics of these different network topologies. All arcs in all networks were assumed to have capacities of four units that if impacted by disaster either decreased by 50 or 100 percent, determined randomly assuming a binomial distribution. Travel times were assumed to increase by 100 or 400 percent, consistent with the chosen capacity reduction.

Three sets of recovery activities were considered under all runs. In the first set, each activity raises the capacity of the arc to which it is applied by one unit, decreases the arc's travel time by two units, requires one unit of time for its implementation and costs \$10. The second set results in increased capacity of two units and decreased travel time of four units. Each activity in this set requires two units of time for its implementation and costs \$25. The third set results in increased capacity of three units and decreased travel time of six units. Each activity requires two units for its implementation and costs \$50.

Three disaster scenarios were considered, the first impacting a randomly chosen set of five arcs, the second impacting a randomly chosen set of half the network arcs and the third impacting all network arcs. Four budget levels were applied: \$0, \$200, \$500 and \$1500. In addition, it is assumed that 16 units of flow (each unit of flow corresponding to, for example, a train) seek the use of the network. These units are evenly distributed across possible O-D pairs. The maximum allowable travel time, $T_w^{\max}$, is assumed to be 50 percent above path travel time requirements under normal conditions for all O-D pairs.

Results of these experiments are given in Table 4-5. Five hundred runs were made for each specification. Each run required less than one minute of computational time.

Table 4-5 Computational results

Networks	# of arcs impacted	Budget	Resilience level (%)
Complete	5	\$0	100
	5	\$200	100
	5	\$500	100

	5	$1500	100
	Half	$0	99.1
	Half	$200	100
	Half	$500	100
	Half	$1500	100
	All	$0	36.0
	All	$200	50.9
	All	$500	84.1
	All	$1500	98.5
Random	5	$0	72.1
	5	$200	98.7
	5	$500	100
	5	$1500	100
	Half	$0	54.0
	Half	$200	59.7
	Half	$500	83.4
	Half	$1500	100
	All	$0	10.1
	All	$200	35.3
	All	$500	83.8
	All	$1500	98.3
Grid	5	$0	85.5
	5	$200	98.7
	5	$500	100
	5	$1500	100
	Half	$0	62.3
	Half	$200	72.5
	Half	$500	92.1
	Half	$1500	100
	All	$0	15.3
	All	$200	47.7
	All	$500	71.6
	All	$1500	99.0
Hub-based	5	$0	95.2
	5	$200	98.8
	5	$500	100
	5	$1500	100
	Half	$0	65.6
	Half	$200	86.8
	Half	$500	93.5

	Half	$1500	100
	All	$0	12.4
	All	$200	75.0
	All	$500	94.2
	All	$1500	100

The results show that for each network, the level of network resilience decreases dramatically with the severity of disruptions and increases with the growth of recovery budget. If a significant number of arcs in the network are impacted and no recovery activities can be undertaken, all networks exhibit poor performance. That is, the LOS constraints cannot be met for most O-D pairs. With an appropriately set budget, network resilience levels greatly improve. These findings are consistent with those from tests of the Double-Stack Container Network.

The experimental results also indicate that complete networks are very resilient. Such networks exhibit high levels of redundancy. Random networks with average indegree or outdegree of two were found to be the least resilient among the four tested network classes. The tested random network included few alternative routes between O-D pairs. Random networks with higher average degree will likely be more resilient. In nearly all tests, the hub-based network was more resilient than the grid network, especially when recovery activities could be undertaken. It appears that the nature of hubs, which are associated with the majority of network connections, plays a role in the network's resilience level. Unless critical links connecting pairs of hubs are impacted, connectivity is maintained for most node pairs even when many links are impacted. If recovery activities can be undertaken, critical links in the hub-based network will consistently be chosen for repair, restoring normalcy with narrowly focused recovery actions.

4.6 Conclusions and extensions

From the perspective of both researchers and practitioners, disaster recovery is considered by some to be the least understood aspect of emergency management (e.g. Berke et al., 1993). In this chapter, a quantitative, system-level indicator of network recovery capability was proposed. A definition of resilience for intermodal freight networks was developed and a stochastic, mixed integer program was formulated. Concepts of Monte Carlo simulation and Benders decomposition were integrated to produce a technique for its solution. The solution methodology was employed in a set of computational experiments performed on the Double-Stack Container Network in which recovery activities that could be undertaken immediately, requiring relatively short implementation time, were considered. These experiments illustrate the resilience concept and show that post-disaster activities can greatly improve resilience levels, and thus, mitigate the negative impact of disasters. The results also indicate that recovery activities are critical to a network's ability to recover and cannot be neglected. Competing measures, such as reliability and flexibility that do not consider recovery actions may underestimate the network's ability to cope with unexpected events. In fact, a network may not be very reliable or flexible, but may be resilient or may be reliable or flexible, but not sufficiently resilient.

The resilience concept was also applied in experiments involving four carefully designed networks with dissimilar topological structures, including complete, hub-based, grid and random structures. Results of these experiments indicate that topological structures with limited redundancies faired worst given a lack of available funds for taking recovery actions; however, even with limited or more modest budgets, improvements in network resilience levels could be obtained. Additionally, greatest improvements were achieved in those networks where few actions might lead to restoration in connectivity between the largest number of O-D pairs, as is the case in a network with hubs. Thus, these experiments indicate that network structures that traditionally fair poorly when reliability is considered can, with only limited recovery action, perform reasonably well, as recovery actions can be focused on highly critical links. This also indicates that pre-disaster planning might be warranted for such networks to ensure that such actions can be quickly and inexpensively taken in the aftermath of disaster.

Modifications to the problem formulation and solution approach may be desired to consider recovery activities that are available only under specific scenarios. Such modifications would entail adding a dimension to the recovery activity selection variables within the formulation. The proposed solution technique could be immediately adapted for this purpose.

This work was motivated by security and mobility concerns in the Washington, D.C.-New York freight corridor, one of the nation's most critical freight transport lifelines. New York is home to one of the largest concentrations of transportation facilities in the world, including three major airports, dozens of container and intermodal yards and more than 11,000 miles of highways (Holguin-Veras, 2000). With both the nation's capital and a global financial center, this corridor is particularly susceptible to terrorist attack. Moreover, as the corridor runs along the coast, it is susceptible to natural hazards. The proposed solution framework employs an exact procedure over a set of network states for each disaster scenario. As the network resilience problem given only one possible network state is NP-hard, exact solution for large, real-world networks, such as the Washington, D.C. – New York corridor, will be difficult to obtain. To decrease the computational effort required, one might consider only the highest priority O-D pairs. Such consideration would require only a nominal change in the objective function. Additionally, in this work, recovery activities associated with individual arcs are considered. Instead of considering all possible combinations of recovery activities associated with all arcs, a subset of these combinations can be considered. Alternatively, a heuristic may be employed for computing the resilience of large networks. The proposed technique can be used to provide exact solution on a set of benchmarks to which the heuristic solutions can be compared.

Specific details of the types of resilient-building activities that can be undertaken prior to, or in the immediate aftermath of, a disaster, such as increasing transportation system diversity and promoting intermodalism, increasing network redundancy and connectivity, hardening facilities to withstand extreme conditions, and preparing backup fleets and personnel, should be further explored. Through sensitivity analysis, it may be possible to identify critical system components and obtain valuable information that can be used in prioritizing activities to be undertaken. Additional efforts may also be expended to extend the proposed resilience concept for use in passenger transport systems.

The focus of this work is on measuring network resilience as it concerns network performance in the immediate aftermath of a disaster. It is presumed that all actions will be reactive, require relatively limited time for implementation, can be implemented immediately and are taken in the aftermath of disaster. It may be beneficial, however, to take some preparedness actions, i.e. proactive measures, prior to disaster occurrence and before the random attributes of the disaster scenario are realized. Such actions may include changes that impact network structure, such as added capacity or redundancies, or that enhance opportunity for quick recovery, such as relocation of supplies for more immediate access in the event of disaster. These actions would be determined in the first stage. Program (P) can be modified for this purpose.

While not the focus of this work, one might extend this work to consider long-term recovery and reconstruction. Such considerations would require a dynamic network model, where capacity is recaptured over time, and time-dependent arc traversal times and capacities that reflect changes in network performance as post-disaster conditions improve. This can be the subject of future research. Additionally, one might consider travel time as a function of link flows; however, the resulting formulation will likely be nonlinear.

Chapter 5   Optimal Team Deployment in Urban Search and Rescue

5.1 Introduction

In this chapter, the problem of optimally deploying federal, state and/or local urban search and rescue (USAR) teams with required equipment and other resources to disaster sites in post-disaster circumstances is studied. USAR equipment includes: cranes, bulldozers, tow trucks, bracing, generators, boats, helicopters and other large heavy equipment; cutting tools; canine units; robots, infrared detection devices, heat sensors, sonar, probes, microphones, remote fiber-optic cameras, and other technologies; and medical supplies (Olson and Olson, 1987; Alexander, 2002). USAR teams must locate, extricate and provide emergency medical assistance to people who have become trapped or wounded in the disaster and are in need of either medical assistance or assistance in escaping (FEMA, 2006). The primary focus of this work is in USAR for large-scale (area-wide) urban disasters caused by natural (e.g. hurricane, tornado, earthquake, or flooding) or human-induced (accidental or terrorist) events, where key decisions relating to search and rescue must be made quickly. In such large-scale disasters, local response capabilities are often overwhelmed and state and national, and sometimes international, resources are required to serve the acute demand for response and rescue.

It is often the case where an urban area has been struck by disaster that the impact area contains numerous sites, such as where buildings or other structures suspected of housing people stood prior to the disaster, where survivors may be trapped. Lessons learned from first-hand experience in USAR activities following three natural disasters in 1985 and 1986 are presented in (Olson and Olson, 1987): the Mexico City earthquake that involved hundreds of failed buildings; the Nevado de Ruiz volcanic eruption and ensuing lahar in Colombia that buried approximately 80 percent of the city; and the San Salvador earthquake involving the collapse of eight major structures. Similar experience was noted following each of two earthquakes with epicenters in Turkey that occurred in 1999 to which U.S. FEMA task forces were deployed (FEMA, 2006). More recently in 2008, the Wenchuan earthquake in China caused 80% of the buildings in the earthquake zone, which included multiple cities, to collapse, burying thousands of people. Numbers of local, national and international search and rescue teams joined the rescue efforts in the days following the disaster (Zhang and Jin, 2008). 250,000 residences and 30,000 commercial buildings collapsed or were severely damaged as a result of an earthquake in the Haitian capital of Port-au-Prince in 2010. The extent of structural damage is depicted in Figure 5-1 (UNOSAT, 2010). USAR support was sent from around the globe. These area-wide disasters involved numerous structural failures, hundreds to tens of thousands of difficult to locate victims requiring extrication and emergency care, damaged infrastructure, and disrupted societies. When the number of sites requiring emergency response assistance outnumbers the number of USAR teams that can be deployed, decisions must be made on the ordering of site visits and team assignment to the sites.

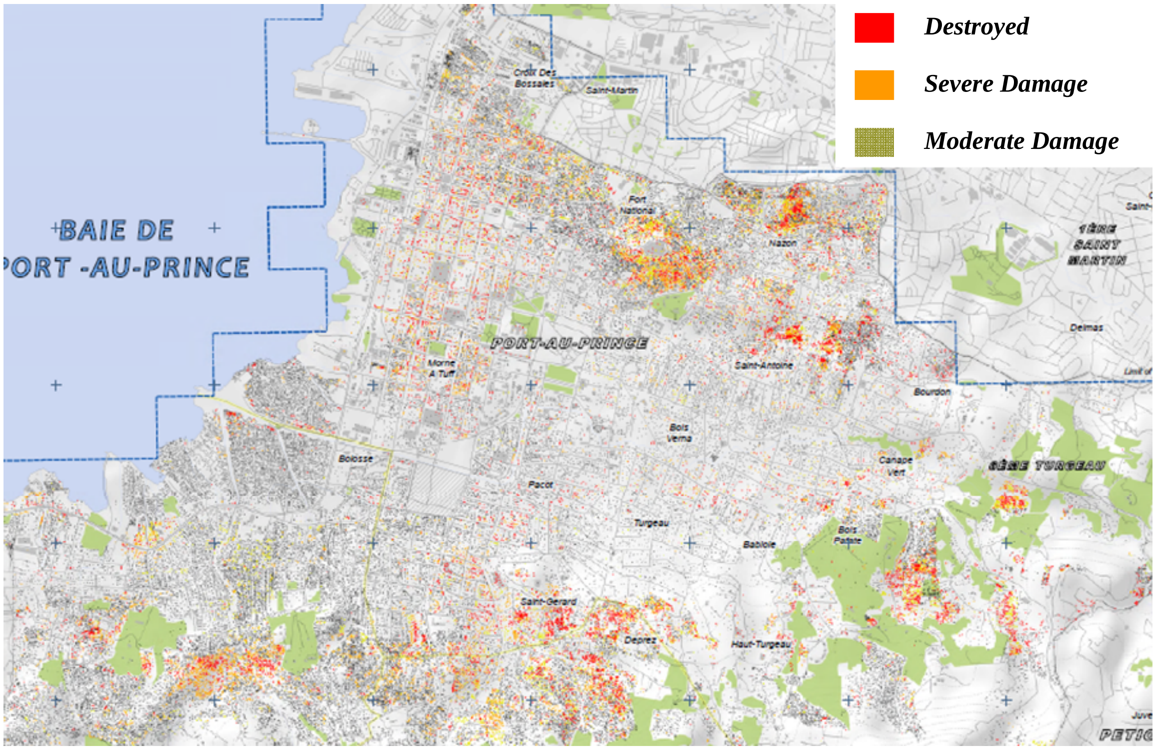


Figure 5-1 The building damage map of Port-au-Prince, Haiti following the 2010 earthquake

Statistics show that 90% of all survivors of disaster are saved within the first few hours of an incident. Following the 1976 Tangshan earthquake, the survival rate declined from 81% to 7.4% between the first and fifth day (Olson and Olson, 1987) post-disaster. Given the fact that the likelihood of finding survivors at any location decreases over time (Olson and Olson, 1987; Noji, 1997; Poteyeva et al., 2007; Barton, 1969), decisions on which disaster sites to visit and the order in which to visit the sites will impact the number of survivors who can be saved. Generally, one would prefer to visit a site where many people with a high likelihood of survival are present than a site where few people are present and the likelihood that any of them are alive and can be saved is low so as to save the largest number of people. This sentiment is well captured in the following statement.

> "Indeed, as cruel as it may sound, local decisionmakers in a disaster may have to engage in what might be called 'structural triage'; that is, because the demand for urban heavy rescue will certainly exceed capabilities, UHR resources will have to be concentrated on those sites where the lifesaving 'payoff' appears highest (Olson and Olson, 1987)."

FEMA supports 28 federal USAR task forces across the U.S. When a governor requests the assistance of the FEMA task forces and FEMA grants the request, the closest task forces and those on rotation are sent. Each task force consists of specially trained fire and rescue personnel, physicians, paramedics, structural engineers, canine handlers, crane operators, and other personnel and each task force is supplied with heavy- and light-rescue equipment. State-level USAR task forces with similar training exist in some states. In addition, numerous voluntary organizations whose members are specially trained for USAR operations exist in all states within the U.S. (Poteyeva et al., 2007). For simplicity, these organizations are classified as state USAR resources herein. Should an event require the response of both state and federal USAR task forces, each task force is treated as a resource for the incident commander. The incident commander, a local fire chief, if a fire is active, or even the mayor, collects real-time information, communicates with the task forces and manages the response.

Determining an effective team deployment strategy for managing the response is challenging. Circumstances immediately following disaster are often physically hostile and mentally confusing, making well reasoned decisions difficult. Moreover, decisions must be taken quickly despite that the number of possible actions/policies that must be considered can be quite large. An effective response, though, is crucial to saving lives. For example, following the 2003 earthquake in Bam, Iran, hundreds of teams from national governmental agencies, 44 foreign countries, the United Nations, and other non-governmental organizations arrived at the disaster region. Despite the tremendous response, significant fatalities were incurred due to delays in the deployment of available USAR resources as a result of a lack of coordination (Ramezankhani and Najafiyazdi, 2006).

In this chapter, the problem of determining the optimal deployment of USAR teams to disaster sites within the disaster region, including the order of site visits, with the ultimate goal of maximizing the expected number of saved lives over the search and rescue period, referred to herein as the USAR team deployment problem (USAR-TDP), is addressed. The need to model the uncertain nature of conditions inherent in situations requiring USAR stems from a multitude of factors, the most significant of which is the uncertainty in the time required to extricate survivors from each site and knowledge of site locations. The USAR-TDP is formulated as a multistage stochastic program (MSP). The demand site and time for extrication are random quantities and new sites containing additional demand for help (referred to herein as demand arrivals) may emerge randomly over time. USAR teams arrive at the scene over the decision horizon. Finally, survival rates diminish with the passage of time. Decisions are taken dynamically over the decision horizon as situational awareness improves. At the beginning of the decision horizon, a subset of disaster sites with a positive number of survivors is known. The incident commander determines sets of tours based on the available demand information, travel times, and stochastic on-site service times. The tours must be rapidly determined. When new demand arrivals become known, and service times are revealed at visited sites, the incident commander will update the tours with the aim of increasing the expected number of served lives.

This depiction of the USAR-TDP, in addition to considering problem dynamics, explicitly addresses the inherent variability encountered in situations requiring USAR operations. Uncertainty in demand and time for extrication is due to the fact that little is known at the onset of the disaster about the number, location, or medical condition of the victims. The likelihood of finding and extricating survivors at a particular site can only be known probabilistically prior to arrival at the site.

A column generation-based methodology employed to solve a sequence of interrelated two-stage stochastic programs with recourse is proposed for the solution of USAR-TDP. Such solutions can aid the incident commander in determining the best deployment strategy for available USAR task forces by directing crucial assets to sites within the impact area, where the most good can be done in the first days of the emergency period.

Related works are discussed in the next section. This is followed by problem definition and discussion of related properties. Details of the proposed solution procedure are presented in Section 5.4. The technique is applied on an illustrative example, results from which are discussed in Section 5.5. Finally in Section 5.6, contributions and potential extensions are discussed.

5.2 Related Research

Few works in the literature consider optimization in search and rescue operations (see, for example, Gal, 1979; Alpern, 2005; Jotshi et al., 2008) and these works propose random search techniques for military and maritime applications, where the objective is to locate a missing person or object. Such formal search theory does not provide direct benefit for solving the USAR-TDP, because the potential search locations (i.e. the sites) can typically be quickly identified. The dynamic resource allocation problem related to the initial search and rescue period with the goal of minimizing fatalities over the time horizon was considered in Fiedrich et al. (2000). A integer program was developed with a nonlinear objective function in which fatalities are calculated over a time horizon and assignment constraints. Heuristics using concepts of both simulated annealing and tabu search were implemented for its solution. No other optimization-based works in the literature were found with direct application to the USAR problem addressed herein.

While there is rather extensive literature related to other emergency response applications, more commonality exists with other, seemingly unrelated problem classes. Thus, this review focuses on the more related areas of dynamic routing and scheduling, and dynamic resource allocation. Problem dynamics must be considered because consideration of uncertainty alone can only facilitate pre-planned solution (Kenyon and Morton, 2003). Finally, routing problems with rewards, including the time-dependent, but deterministic team orienteering problems, are also reviewed as, if appropriately modified to handle random inputs and employed within a dynamic framework, solution methods developed for this class of problems may have applicability in solving the USAR-TDP.

Dynamic routing and scheduling problems have been studied extensively. They fall into the class of on-line routing problems. Such problems are characterized by dynamics associated with service requests that arise over the problem horizon and stochasticity in information pertaining to, for example, customer presence, customer demand, travel times and service times, that cannot be known at the time of planning, or are only revealed as time progresses. Such information can be described by random variables with known probability distributions. An overview of works addressing dynamic routing and scheduling problems can be found in (Psaraftis, 1995; Bertsimas and Simchi-Levi, 1996; Gendreau and Potvin, 1998; Ghiani et al., 2003; Laporte, 2009). Powell (1995), in addition to reviewing these works, described the advantages of dynamic models over comparable static models for these problems and discussed various approaches to dealing with uncertainty.

In the related literature, problem dynamics are tackled either by myopic approaches (e.g. Mahmassani et al., 2000; Larson et al., 2002; Chen and Xu, 2006) or by look-ahead procedures (e.g. Larson et al., 2004; Mes et al., 2008). In the more myopic approaches, routing plans are developed based only on available information at time of decision; the possibility of new customers arriving in the future is, thus, ignored. Such methods are suitable for situations where future events are difficult to forecast. On the contrary, look-ahead procedures take probabilistic information concerning the future into account so as to improve performance over the time horizon. Mitrovi´c-Mini´c and Laporte (2004), and Branke et al. (2005) show that pre-positioning vehicles in anticipation of future demand can lead to greater probability of servicing future potential customers. Bent and Hentenryck (2004) found that significant gains were produced by considering the possibility of randomly arriving customers over the future with respect to the dynamic vehicle routing problem. These approaches require estimates of arrival process probability distribution functions.

A special case of dynamic, stochastic vehicle routing problems is the dynamic traveling repairperson problem (DTRP) originally proposed by Bertsimas and Van Ryzin (1989). In this problem, vehicles must service customers that arrive according to a Poisson process. Customers require stochastic on-site service time. Bertsimas and Van Ryzin (1991) considered the system as a spatially distributed queueing system and looked for a single routing policy that minimizes the expected time customers must wait for service completion given known probability distributions of random service times. Larsen et al. (2002) examined routing policies for the partially dynamic DTRP in which some customers are known in advance while others arrive while the vehicle is en route.

Two general modeling frameworks that account for sequential realized random variables are commonly used: multistage stochastic programs with recourse (e.g.

Frantzeskakis and Powell, 1990; Chueng and Powell, 1996) and Stochastic dynamic programs with discrete time (e.g. Gendreau et al., 1999; Yang et al., 2004; Chen and Xu, 2006). A number of techniques are applied for the solution of multistage stochastic programs with recourse. These techniques can be classified into one of several categories: solution of the deterministic equivalent formulation (a computationally intractable approach often resulting in unnecessarily expensive solutions), sampling methods (which explicitly enumerate the space of possible outcomes), the deterministic mean method (replacing every random variable with its mean value), approximation methods (approximating the recourse function as a set of linear functions or as a piecewise linear and convex function), and decomposition methods (which decompose the original problem into a collection of deterministic sub-problems usually governed by a master problem). The majority of solution techniques found in the literature that build on these general classes of approaches are, however, heuristic. Various heuristics have also been proposed in the literature to address stochastic and dynamic program, including rule-based heuristics, metaheuristics such as tabu search and genetic algorithms, approximation dynamic programming, scenario-based methods and mathematical programming-based methods.

In the dynamic resource allocation problem (DRAP), tasks arriving over time must be covered by a set of indivisible and reusable resources of different types. The arrival process of tasks is known only through a probability distribution. Each task requires a certain amount of resources and produces an associated reward. Such problems are often modeled as either dynamic assignment problems or dynamic and stochastic knapsack problems (DSKP).

The dynamic assignment problem can be viewed as an instance of the dynamic resource allocation problem, where a complex resource (e.g. a vehicle) must be dynamically assigned to tasks (loads) that arise randomly over time. Powell (1996) formulated the dynamic assignment problem in the context of load-matching for truckload trucking using a nonlinear approximation of the future value of resources. Powell et al. (2000) proposed a myopic model and algorithm for the dynamic assignment problem of routing a driver through a sequence of customers with loads in the context of truckload trucking. Spivey and Powell (2004) proposed a more general class of dynamic assignment models and developed an adaptive algorithm to iteratively solve a series of interrelated assignment problems.

Kleywegt and Papastavrou, among others, have proposed solution techniques for the DSKP (1996, 2001). Demand (constraining the problem) arises randomly over time and resources for serving the demand (i.e. items to pack in the knapsack) become available over time. Each unit of demand requires a specific amount and type of resource and has an accompanying reward that is unknown before arrival. The objective is to determine an optimal policy for serving demand so that the expected total reward achieved is maximized. The problem was formulated as a Markov decision process. Properties of the value functions proposed in each of the works were presented and optimal policies and stopping rules were provided. Lin et al. (2007) studied a set of myopic policies for the DSKP and found that of the studied policies, the best policy is to wait (and not assign resources) until demands with the highest price.

While DRAPs share some properties with the USAR-TDP, the need to route resources is not considered. Time (resources) consumed by items in the DRAP does not depend on the order in which the items are served. Thus, the USAR-TDP, while similar in many respects to the DRAP, has the added complicating factor associated with order-dependent resource needs. To apply solution techniques designed to address the DRAP in solving the USAR-TDP, the solution techniques would need to consider the arrangement of items within the knapsack, as how the items are arranged will affect the space they occupy (i.e. the time required to complete the route). Moreover, the capacity filled by these items would be time-dependent (as travel time is time-dependent in the USAR-TDP). Similarly, the exact and heuristic techniques for solving dynamic routing and scheduling problems cannot be applied directly in solution of the USAR-TDP, because they do not account for the need to visit only a subset of identified customers so as to maximize the rewards gained by visiting each customer. The DVRP can be considered as a special, less complicated case of the USAR-TDP. Incorporating the decreasing survival likelihood endemic in the USAR-TDP cannot be addressed by techniques devised for either dynamic resource allocation or dynamic routing and scheduling problems.

Another class of problems with possible relation to the USAR-TDP is the class of selective routing problems. The Team Orienteering Problem (TOP) is a well-known reward-collecting problem (a type of selective routing problem) that seeks a set of *m* vehicle tours restricted by a pre-specified limit such that the total reward received from visiting a subset of customers is maximized. A number of heuristics have been proposed for the TOP: a greedy construction procedure (Butt and Cavalier, 1994), the 5-step heuristic (Chao et al., 1996), a tabu-search based heuristic (Tang and Miller-Hooks, 2005) and an ant colony optimization approach (Ke et al., 2008). The only two exact algorithms that address the TOP are based on column generation (Butt and Ryan, 1999) and branch-and-price (Boussier et al., 2007). A closely related problem, with greater relevance to the USAR-TDP, is the maximum collection problem with time-dependent rewards (MCPTDR). In the MCPTDR, the sequence of customers to be visited for one vehicle over multiple days is determined so as to maximize the total collected rewards (Tang et al., 2007). Erkut and Zhang (1996) addressed a related problem in which rewards are assumed to be monotonic decreasing functions of time. They developed a branch-and-bound-based heuristic for its solution. Other related routing problems in the literature include the prize collecting traveling salesman problem (TSP), TSP with profits, and selective vehicle routing problem (SVRP). These reward collecting problems are more complicated than the well-known TSP or VRP in the sense that not only tour must be planned, but also a subset of customers must be selected for routing and assignment.

The USAR-TDP considered herein can be modeled as a MCPTDR with multiple vehicles (i.e. USAR teams) and rewards that strictly decrease over time (due to decreasing likelihood of survival). Each customer in the MCPTDR represents a disaster site. To capture problem dynamics (i.e. evolving information concerning demand arrivals and estimated on-site service times), the technique developed by Tang and Miller-Hooks can be embedded within a rolling horizon framework to capture problem dynamics (minor modifications would be required to incorporate multiple teams). Uncertainty in site service times cannot be easily addressed, however.

To the best of the author' knowledge, no other work in the literature with greater relevance than those reviewed herein exists and no work in the literature can be directly applied to solve the USAR-TDP.

5.3 USAR team deployment problem

In this section, the USAR-TDP is defined and a multistage stochastic formulation of the problem is presented. The USAR-TDP is characterized by the fact that demand arises continuously and randomly over a decision horizon, often at a pace that exceeds available resources. Thus, this requires the incident commander to make life-and-death decisions as to how these limited resources are to be deployed in an environment where every minute counts.

5.3.1 Stochastic, dynamic search and rescue networks

A network representation of the disaster-impacted area is exploited to formulate the USAR-TDP. In such a network representation, nodes represent potential sites, where survivors who are in need of assistance are likely to be located. The network arcs represent the passageways (e.g. roadways) connecting the sites. Let $G = (\mathcal{V}, \mathcal{A})$ serve as a model of the disaster-impacted region, where vertex set $\mathcal{V} = \{0\} \cup \mathcal{L}$ represents the origin (vertex 0, from which USAR teams are dispatched) and a set of geographically dispersed disaster sites $\mathcal{L} = \{1, 2, ..., L\}$, and arc set $\mathcal{A} = \{(i, j) | i, j \in \mathcal{V}, i \neq j\}$, representing connections between all pairs of locations. Thus, a complete graph is assumed; the shortest path length between each pair of nodes is employed.

The network is considered at a set $\mathcal{H}$ of discrete time periods (i.e. stages) $\{t_0 + h\delta\}$, where $h = 0,1,2,..., H$, and δ is a constant increment of time. $t_0 + H\delta$, defines the last time interval in H and, thus, the decision horizon. It is reasonable to set $H\delta$ to the number of days beyond which there is no hope of finding victims alive. Thus, there are $H + 1$ number of periods in the decision horizon, and $\mathcal{H} = \{0,1,..., H\}$ are the times at which decisions are made. The travel time between sites and on-site service times are assumed to require at least one period that would be half an hour or one hour.

The demand (i.e. the number of survivors requiring assistance) at site i in stage h is denoted by d_i^h. It is assumed herein that the demand size is known deterministically once the demand location is realized because demand forecasts can be made based on the size and use of buildings, as well as materials from which they are constructed, building occupancy. As situational awareness improves with time, new information impacting forecasts of demand arrivals will be received over the course of the search and rescue period and new demand sites will be recognized. It is assumed that no new demand will be generated at a site that is already served, because a USAR team will only leave a site after ensuring there is no remaining demand to serve at the site. The amount of demand generated at such later times relative to the total demand generated over the decision horizon reflects the degree of dynamism of the post-disaster system as defined by Larson (2000) in the context of dynamic vehicle routing problems. Specifically, a probability space $(\Omega, \mathrm{F}, \mathrm{P})$ under which a Poisson arrival process $(N_t)_{t \geq 0}$ with intensity λ is defined. The sequence of demand arrival epochs corresponds to the Poisson process arrival times. It is assumed that demand arrivals only occur at the beginning of a stage.

As the likelihood of survival diminishes over time, there will be a reduction in the number of people seeking assistance (i.e. demand) over time. Consequently, demand decreases with increasing stage number. It is assumed that once a site is visited, all those alive upon the team's arrival on site will require extrication and the number of people to survive will be a function of the arrival stage even if extrication is completed in a later stage. The demand reduction ratio for different stages is given by $\{\gamma_0, \gamma_1, ..., \gamma_H\}$, where $1 \geq \gamma_0 > \gamma_1 > \gamma_2 ... > \gamma_H = 0$. Thus, for demand d_i^h carried from the previous stage, $d_i^h = \gamma_h \cdot d_i^{h-1}$.

Associated with each vertex $i = 1,2,..., L$ is an on-site service time, s_i, for completing search and rescue operations at this site. The on-site service times cannot be known *a priori* as the exact time required for extrication of even one person cannot be known *a priori* of certainty. Service time depends on the number of survivors located on site, working conditions, team make-up and equipment, as well as many other factors. It is not always the case that a larger number of survivors will require longer service time, as one difficult to extricate case may require more time than efforts associated with a number of less difficult to extricate cases. Thus, service time s_i at site *i* is is a random variable with a finite number of discrete, positive and integral support points and is independent of the site demand and time stages. Actual service times are revealed only when USAR team arrives at the site. It is assumed that service can not be disrupted; that is, a team will complete its service at a site before moving on to a new site and any work on site begun prior to the end of the decision horizon will be completed.

A travel time matrix $T = \{t_{ij}^h\}_{(i,j)\in A, h\in H}$ is defined on $A \times H$. Travel times are assumed to be constant over the decision horizon. This assumption is supported by events of the 2010 Haitian earthquake, where few resources were available during the first few days following the earthquake for roadway repair. Moreover, there is no evidence in the reviewed literature that helicopters or other forms of transportation that would quicken the travel times became available for wide use over the decision horizon.

A set of homogeneous USAR teams are available at the depot for deployment over the decision horizon, $K = \{1,2,\ldots,K\}$, where *K* is fixed and indicates the number of available USAR teams. While a portion of these teams will be ready for deployment at the beginning of the decision horizon, some teams may arrive at later stages. It is assumed that the time of arrival of USAR teams over the course of the decision horizon is known *a priori* and any team to arrive to the disaster region over the decision horizon does so at the beginning of a stage. The number of teams available in stage h is denoted by k^h and $K = \sum_{h=0,...,H} k^h$.

Regardless of the magnitude of the disaster, it is expected that the number of sites requiring response is significantly larger than the number of available teams; that is, $L > K$. Thus, it is not advantageous for any team to sit idle at any point in the decision horizon. A team can only receive new instructions upon completion of service at a site. A team can change its destination while en route, but cannot leave a site before completing its work. No more than one team will be assigned to a given site and no site will be visited more than once.

Each team follows a tour, i.e. a sequence of sites $[0, i, ..., j]$, beginning from the depot. The tours need not return to the depot. It is anticipated that each designed tour will cover the span of the decision horizon and no team returns to the depot until USAR operations are complete and the decision horizon has elapsed. That is, the duration of each tour is no greater than H. So that reasonable working conditions are maintained, rescue workers must be provided with opportunities to rest and obtain basic sustenance. Such periods of rest can be accommodated by idling teams at regular periods, but, for simplicity, are not explicitly considered herein. The USAR-TDP seeks a set of K tours through all or a subset of known demand sites located at geographically dispersed locations within the disaster region such that the expected total number of survivors extricated by available USAR teams is maximized.

An important dimension of the USAR-TDP is the evolution of information. As time progresses, the decision-maker gradually comes to know more about the true state of the situation. That is, the sites to be served, new sites entering the system, the time required to extricate survivors become known. Additionally, improved situational awareness can lead to improved future estimates. It is even possible that surveillance teams are deployed within the region to gather information that is then shared with the decision-maker. It is assumed that decisions in stage h must be made using the information available at the time the decision is taken (i.e. prior to stage h). Forecasts for future stages can also be updated based on such information. The reality of the disaster impact is fully realized only at the end of stage H. With the assumptions and definitions in mind, the USAR-TDP is formulated next.

5.3.2 Multistage stochastic formulation

To model the process of decision making given uncertainty in disaster site locations and service times at known locations over a finite decision horizon, a multistage stochastic program is developed. Such multistage stochastic programs capture the information structure that can be represented by scenario trees. At each time period in the decision horizon, each USAR team is either serving a site or en route to a site. When a team completes its work at a site, it becomes available for repositioning to a new site. Whether it will follow the previously planned tour or a new tour is determined. That is, sites can be reassigned between teams and the order of visits can be altered. The following decision variables are defined related to these decisions.

$$x_{ijk}^{h} = \begin{cases} 1, & \text{if a team } k \text{ travels to site } j \text{ directly from site } i \text{ at stage } h, \\ 0, & \text{otherwise,} \end{cases}$$

$$y_{ik}^{h} = \begin{cases} 1, & \text{if a team } k \text{ starts its service at site } i \text{ at stage } h, \\ 0, & \text{otherwise,} \end{cases}$$

Parameters of the model not previously defined are given as follows.

$\hat{d}_i^h$ = demand at site i that is first revealed at stage h, $\hat{d}^h = \{\hat{d}_i^h\}_{i \in L}$

d_i^h = demand at site i that was carried over from a previous stage

$\tilde{d}_i^h$ = demand for USAR service at site i at stage h, $\tilde{d}_i^h = \hat{d}_i^h + \gamma_h d_i^{h-1}$

Let $\xi = (\xi_1, \ldots, \xi_H)$ be a discrete-time stochastic information process over a finite probability space $\{\Omega, \mathrm{F}, \mathrm{P}\}$. An outcome $\tilde{\xi}_h$ sets the realization of random variables for all sites visited (or identified in stage one or higher) prior to stage h. Thus, the history of realizations and decisions can be captured by a state variable $S_h = \{(x^0, y^0), (\tilde{\xi}_1, x^1, y^1), \ldots, (\tilde{\xi}_{h-1}, x^{h-1}, y^{h-1})\}$. A decision (x^0, y^0) is made to satisfy the constraints in stage zero. Thus, a decision vector $z^h = (x^h, y^h) = X(S_h)$ is made then for stage h, where X is a mapping from states to a finite number of decisions. Generally, for any stage h, decisions (x^h, y^h) have to be adapted to the sequential information process S_h. The USAR-TDP can be written as the following multistage stochastic program.

$$Max \quad E_{\xi_1}\left\{\sum_k\sum_i \tilde{d}_i^1 y_{ik}^1 + E_{\xi_2|\xi_1}\left[\sum_k\sum_i \tilde{d}_i^2 y_{ik}^2 + \ldots + E_{\xi_{H-1}|\xi_1,\xi_2,\ldots,\xi_{H-2}}\left[\sum_k\sum_i \tilde{d}_i^{H-1} y_{ik}^{H-1}\right]\ldots\right]\right\} \tag{1}$$

Subject to

$$\sum_k\sum_j x_{0jk}^h = K^h, \tag{2}$$

$$x_{ijk}^h \le y_{jk}^{h+\tau_{ij}^h} \quad \forall i, j, k, \tag{3}$$

$$\sum_j x_{ijk}^{h+s_i^h} \le y_{ik}^h \quad \forall i, k, \tag{4}$$

$$\sum_h\sum_k y_{ik}^h \le 1 \quad \forall i \tag{5}$$

$$\sum_h\sum_i\sum_j \tau_{ij}^h x_{ijk}^h + \sum_h\sum_i s_i^h y_{ik}^h \le H \quad \forall k, \tag{6}$$

$$x_{ijk}^h = \{0,1\}, y_{ik}^h = \{0,1\} \quad \forall i, j, k, h \tag{7}$$

The objective function (1) seeks to maximize the expected number of people that can be saved over the decision horizon. Constraints (2) require that available USAR teams are immediately deployed from the depot. Constraints (3) and (4) are flow conservation constraints, defining the time upon which each team arrives at the assigned site and the time that team is repositioning to other site. As the objective is to maximize total reward, when a team becomes available, it will be assigned to a new site. Constraints (5) require that only one team will serve each site. Constraints (6) enforce the tour length for any team *k* no greater than *H*. Constraints (7) are binary restrictions.

The multistage stochastic programming formulation provides a concise representation of the USAR-TDP. The formulation is anticipative in nature; although, a solution requires forecasts of demand arrival distribution functions for the entire decision horizon. Approximation techniques have been proposed for multistage stochastic, linear programs. These techniques reduce the multistage program to a problem with only a single stage by approximating the series of recourse functions by a single convex function. The MSP formulation of the USAR-TDP employs binary integer variables and recourse functions associated with each stage are nonconvex. Consequently, such an approximation of the recourse function in a single convex function is not possible. Approaches for multistage stochastic, integer programs are few and are generally heuristic or scenario-based. In the next section, a technique that decomposes the multistage stochastic, integer program into a series of two-stage stochastic, integer programs is presented. While solution of each two-stage stochastic program is exact, the solution approach is myopic. That is, it is nonanticipative. As a consequence, the approach can be considered as an approximation approach for the MSP formulation of the USAR-TDP. Such an approximation, however, is reasonable for the considered application, where situational awareness, and thus the ability to forecast demand arrivals, continuously improves with time. Obtaining a single forecast at the beginning of the decision horizon is unrealistic.

5.4 Algorithm

In this study, the proposed solution approach tackles the multistage stochastic programming formulation (1)-(7) by solving a series of inter-related two-stage stochastic programs with recourse, each arising at the beginning of a decision epoch and each exploiting information from solution of the problem at the prior epoch.

5.4.1 The stochastic problem at each decision epoch

The time horizon is divided into M equal-size decision epochs, and $t_0, t_1, ..., t_{i-1}, t_i, t_{i+1}, ...t_M$, with 0= $t_0 < t_1 < ... < t_M = H$, where $t_i \geq \delta$. Thus, decision epochs are composed of $[t_0, t_1), [t_1, t_2), ..., [t_{M-1}, t_M]$. Without loss of generality, it is assumed that the length of a decision epoch, $[t_{i-1}, t_i)$, can be a multiple of increment δ. The number of survivors at a site in a given decision epoch is assumed to remain constant over the epoch. That is, the reduction factor is only applied at the beginning of the epoch in estimating the number of survivors at a given site.

The system state is defined by the locations of the teams (including those teams first arriving at the depot as scheduled, and those en route), remaining on-site service times at these locations, sequences of remaining sites to be visited that are already scheduled, and the locations and estimates of demand arrivals. New information concerning the system state arrives over time. At the beginning of each decision epoch, solution of the two-stage stochastic program given the current system state, provides updated tours for each of the teams. Solutions may involve decisions to add, drop, or resequence sites in tours developed in the previous epoch. Swapping sites among tours is also permitted. Moreover, teams may be diverted from a tour while en route to a site. Future demand arrivals and service times of future site visits are known only with uncertainty at the start of an epoch. Thus, tours are dynamically updated over the decision horizon.

A prototypical multistage stochastic program for the USAR-TDP is given as follows.

$$\begin{aligned} \max \quad & E_{\xi_1}[D^1 z^1 + \ldots + E_{\xi_M \mid \xi_1, \xi_2, \ldots, \xi_{M-1}}] \\ \text{subject to} \quad & Az \le b \\ & z \in \{0,1\}^{|V| \times |A|} \end{aligned}$$

Thus, at time 0, the two-stage stochastic problem is as follows.

$$\begin{aligned} \max \quad & E_{\xi}[DZ] \\ \text{subject to} \quad & Az \le b \\ & z \in \{0,1\}^{|V| \times |A|} \end{aligned}$$

At each time epoch t_i thereafter, i.e. for $i = 1,2,\ldots,M-1$, given realizations of random variables from prior decision epochs $\tilde{\xi}_0,\ldots,\tilde{\xi}_{i-1}$ and decisions taken $\tilde{z}_0,\ldots,\tilde{z}_{i-1}$, the two-stage stochastic problem can be written as follows.

$$\begin{aligned} \max \quad & E_{\xi}[DZ \mid \xi_1 = \tilde{\xi}_1, \xi_2 = \tilde{\xi}_2, \ldots, \xi_{i-1} = \tilde{\xi}_{i-1}] \\ \text{subject to} \quad & Az \le b - \sum_{m=0,\ldots,i-1} A\left(\tilde{\xi}_{i-1}\right) \cdot \tilde{z}_{i-1}, \\ & z \in \{0,1\}^{|V| \times |A|} \end{aligned}$$

The stochastic program at decision epoch t_i is denoted by [SP$_i$], for $i = 0,1,2,\ldots,M-1$. Each [SP$_i$] is defined over the period $[t_i, H]$. At time t_i, given demand arrivals and service times revealed at or before time t_i, [SP$_i$] seeks to generate a set of tours to maximize the expected number of people that can be saved over $[t_i, H]$. The solution will be implemented for the decision epoch $[t_i, t_{i+1})$ and the system state is revealed at the end of the decision epoch. Solution of each succeeding [SP$_i$] will yield a higher expected reward compared with using the tours developed with information from a previous decision epoch, because the optimal solution from a prior decision epoch is guaranteed to be feasible for future decision epochs. Under perfect information, the solution generated by [SP$_0$] is equivalent to the solution of the multistage stochastic formulation. The complexity of the proposed solution technique grows linearly with the number of stages and is found to be reasonably fast in computational experiments. The general approach of solving a multistage stochastic program by reducing the problem to a series of two-stage stochastic programs with diminishing decision horizon was discussed by Chen and Homem-de-Mello (2008) in the context of airline revenue management.

Future demand arrivals that may be revealed in a future decision epoch are not considered in the current epoch. The set of disaster sites in need of assistance at time t_i is composed of the set of unvisited disaster sites with positive demand at or before t_i and the set of demand arrivals occurring in the time interval $(t_{i-1}, t_i]$, denoted by B_i. This problem does not account for the potential impact of its solution on future demand arrivals. It is noted that not all USAR teams are available in the disaster region at the decision epoch t_i. Some teams will arrive later with a known arrival time. However, all the teams can be considered as available at the depot from time 0, but travel times to disaster sites can be increased to account for the arrival time of teams arriving later. Thus, for each decision epoch, all *K* teams are considered and *K* tours will be constructed so as to maximize the expected number of people saved.

Alternatively, one can consider updating the solution as teams become available for reassignment rather than at fixed intervals of time. There are tradeoffs in computational requirements between resolving when each team completes each job and resolving at fixed time increments. The solution technique described in the following section can accommodate either representation. Moreover, it is not required that decision epochs be of equal length.

5.4.2 The set-partitioning-based formulations

In this section, a column generation-based approach is proposed for solving the USAR-TDP by reduction to a series of interrelated two-stage stochastic programs with diminishing decision horizon. This technique builds on findings from work by Chen and Xu (2006), where similarities between solutions of consecutive decision epochs are exploited in a reoptimization-like approach. That is, a solution from decision epoch i provides a starting place for a solution in decision epoch $i+1$. Chen and Xu applied this technique for solution of the dynamic vehicle routing problem. Experimental results showed the efficiency of this technique.

The problem to be solved at each decision epoch, [SP$_i$], is a two-stage stochastic mixed-integer program with recourse. In stage one, each team follows its planned tour until either all the site visits on this tour are completed, or upon reaching the end of the decision horizon H. It is assumed that all the random variables pertaining to on-site service times are revealed, i.e. scenarios are considered, and stage two begins with the implementation of a set of recourse actions that maximize the expected reward associated with serving the remaining disaster sites for the given scenario. Thus, *a priori* tours are sought that perform best given the set of considered stage two scenarios. Such solutions are said to be robust. One can view decisions taken in future epochs as a form of recourse action as considered in stage two.

[SP$_i$] must be reformulated by Dantzig-Wolfe decomposition to construct specially-structured sub-problems suitable for solution by a column generation-based technique. A decision variable is associated with each feasible tour. Each tour is associated with a column in the formulation and the objective is to select a set of columns to generate the maximum reward such that each disaster site is covered by exactly one column. Thus, [SP$_i$] is formulated as a set-partitioning-based program, as described in the following subsection.

5.4.2.1 Two models with/without recourse

The objective of the two-stage stochastic problem, [SP$_i$], that arises at each decision epoch is to construct a set of k planned tours with maximum expected reward. The maximum expected reward is computed from the sum of R_u from first-stage decisions and scenario-dependent probability-weighted rewards achieved through second-stage recourse actions all totaled over the decision horizon.

As the random on-site service times are revealed, it may be found that it will not be possible to complete some tours. When this arises, the tour is said to fail. Such failure occurs, thus, whenever the realized cumulative tour length in terms of travel times and service times exceeds the end of the decision horizon H. Failure is not an indication of infeasibility, but rather notification that actual rewards will be less than expected and recourse actions that reassign unvisited sites along failed tours may be advantageous. A recourse strategy that assigns unvisited sites from failed tours or incorporates unassigned sites when teams become available earlier than expected is implemented in the second stage.

Given the planned set of disaster sites to be visited on a tour, the stochastic program is augmented with a set *W* of scenarios, where each scenario represents a realization of the random on-site service times. Let $U_k(t_i)$ be the set of feasible tours for team *k*, with $\bigcup_{k\in K} U_k(t_i) = U(t_i)$. Under different realizations, all or a subset of pre-planned sites will be served during stage one. The model is further augmented by inclusion of partial tours with additional sites that can be served by augmenting the original assigned tour $u \in U_k(t_i)$ if the team *k* completes its assigned tour before *H* given the realization of service times in scenario *w*.

Each tour $u \in U(t_i)$ is defined as an ordering of visits to a select set of sites. The objective of [SP_i] is to maximize the expected number of people saved over the decision horizon $[t_i, H]$. Each such person is referred to as a reward. Thus, one can view this problem as that of maximizing the total expected rewards. Because service times at each site are uncertain, one cannot know *a priori* the reward that will be obtained upon completion of a tour. Instead, one can compute the expected reward, R_u, associated with a tour $u \in U(t_i)$ over all possible service time scenarios.

To formulate the USAR-TDP as a set partitioning problem, the following additional notation is employed.

ξ = A vector of random on-site service times with a finite number of realizations, $\xi^1, \xi^2, ..., \xi^W$, where W is the number of realizations (i.e. scenarios) of vector ξ;

p_w = The probability that the random vector ξ takes on the scenario $w \in W$;

C_u^w = Set of partial tours designed to augment tour *u* under scenario $w \in W$;

C^w = Set of all partial tours developed for scenario *w*, $C_w = \bigcup_u C_{\tilde{u}^w}$;

$$\delta_{iu} = \begin{cases} 1 \text{ if a site } i \in B_i \text{ is covered by a planned tour } u; \\ 0 \text{ otherwise}; \end{cases}$$

$$\alpha_{iu}^w = \begin{cases} 1 \text{ if a site } i \in B_i \text{ is covered by the realization of tour } u \text{ in scenario } w; \\ 0 \text{ otherwise}; \end{cases}$$

β_{icu}^w = 1 if a site $i \in B_i$ is covered by a partial tour $c \in C_u^w$ in scenario *w*, 0 otherwise;

R_u = Expected reward of tour $u \in U(t_i)$;

r_{cu}^w = Reward associated with partial tour $c \in C_u^w$ in scenario *w*;

x_u^k = 1 if the planned tour $u \in U_k(t_i)$ is selected for team *k*, 0 otherwise;

y_{cu}^w = 1 if $c \in C_u^w$ is selected under scenario *w*, 0 otherwise.

The USAR-TDP for a given decision epoch considering recourse operations is formulated as follows.

[SP$_i$]
$$Max \quad \sum_k \sum_{u \in U_k(t_i)} R_u \cdot x_u^k + E_\xi\left[Q\left(x, \xi^w\right)\right] \tag{8}$$

subject to

$$\sum_{k \in K} \sum_{u \in U_k(t_i)} \delta_{iu}^k \cdot x_u^k \le 1, \quad \forall i \in B(t_i), \tag{9}$$

$$\sum_{u \in U_k(t_i)} x_u^k = 1, \quad \forall k \in K, \tag{10}$$

$$x_u^k = \{0,1\}, \quad \forall u \in U_k(t_i), k \in K. \tag{11}$$

where, the conditional recourse function is given by,

$$Q(x, \xi^w) = \quad Max \quad \sum_{u \in U(t_i)} \sum_{c \in C_u^w} r_{cu}^w y_{cu}^w \tag{12}$$

subject to

$$\sum_{u \in U(t_i)} \alpha_{iu}^w \cdot x_u^k + \sum_{u \in U(t_i)} \sum_{c \in C_u^w} \beta_{lcu}^w \cdot y_{cu}^w \leq 1, \quad \forall i, w, \tag{13}$$

$$x_u^k - \sum_{c \in C_u^w} y_{cu}^w \geq 0, \quad \forall u \in U(t_i), \tag{14}$$

$$y_{cu}^w \in \{0,1\}, \quad \forall c \in C_u^w, u \in U(t_i), w \in W . \tag{15}$$

The objective function (8) is to maximize the expected reward of the planned tours plus the expected second-stage reward gained by optimally visiting additional disaster sites given each scenario. Since all the uncertainty is revealed at the end of stage one, the expected reward of the extra tours can be computed from the expected sum of the reward at the additional sites that can be served for each scenario. Constraints (9) requires that each disaster site is covered by at most one tour, while constraints (10) ensure one and only one tour is selected for each team. The conditional recourse function (12) is to maximize the reward gained by visiting additional sites for each scenario. Constraints (13) ensure that each site is served by at most one team for each scenario. Constraints (14) require that one and only one additional tour is selected if one an *a prior* tour is implemented. Binary integrality constraints are given in constraints (11) and (15).

[SP$_i$] is a two-stage stochastic program with simple recourse. The first-stage variables are x_u^k and second-stage variables are y_{cu}^w. At the end of the first stage, the visited sites, final position and remaining service times associated with each team are known. Partial tours (i.e. second-stage variable) can be generated to improve the objective function value. The formulation takes the possible interactions between teams into account through recourse actions. Such interactions might involve the swapping of sites between tours of two teams, or perhaps the move of a site from one team's tour to another team's tour. Thus, changes in one tour may impact the other. The impact of such interactions or interchanges is evaluated through consideration of recourse actions.

If when setting all random service times to their expected values, the total completion time of the tour is greater than H, this tour is considered to be infeasible in expectation. In this study, it is assumed that the formulation does not include tours in the first stage that are infeasible in expectation. If including tours that are infeasible in expectation, it is very likely that most teams cannot complete their tasks or teams finishing earlier will not have enough time to cover additional sites. In this case, the impact of considering recourse actions will be marginal. On the other hand, if tours are generated conservatively by, for example, assuming that site service times will be long, as would be the case if the upper bounds on the service times were employed in generating feasible tours, recourse actions are likely to be needed. In fact, very few sites will be included in the tours developed in the first stage. By postponing future routing decisions to the second stage, the problem is effectively reduced to solving a set of scenario-dependent, deterministic problem instances.

This problem can be simplified if recourse actions are not considered and, instead, *a priori* tours are determined assuming that the tours will be followed without change. The simplified formulation is obtained by dropping the recourse function.

$$[SSP_i] \qquad Max \quad \sum_k \sum_{u \in U_k(t_i)} R_u \cdot x_u^k \tag{16}$$

subject to

(9),(10),(11)

The objective function (16) is to select a set of columns with maximal expected reward. Any tour $u \in U_k(t_i)$ will include as many sites as possible to improve the expected reward of the tour. Thus, tour can be generated by using the lower bounds of service times. Such tours fail in expectation and could fail under a specific realization of service times. Any solution to [SSP$_i$] is a feasible solution to [SP$_i$]; that is, [SP$_i$] provides a better plan of the expectation of saving more people's lives by taking teams' interactions into account.

The set partitioning-based formulations contain a vast number of tour variables. To solve the problem to optimality, all possible feasible tours would need to be generated. The number of possible tours increases exponentially with increasing number of sites, making it difficult to solve real-world size problems. To address the difficulty associated with this feasible tour generation, a column generation-based approach is proposed and described in the Section 5.4.3.

5.4.2.2 The expected reward of an a priori tour

Suppose that a tour $\{0, L_1, L_{2,...,} L_n\}$ is assigned to a team. It will be followed in numerical order, $0 \to 1 \to 2 ... j \to j+1 ... \to n$. Let a_i be the arrival time at site *i*. a_i is important for evaluating the expected reward of an *a priori* tour because the number of people requiring service at site *i* diminishes over time. The earlier a site is visited, the larger the number of people that can be saved. Let g_i represent whether or not a site *i* is served given first-stage decisions and revealed service times at the end of the first stage. g_i equals one if the site has been served and zero otherwise. On-site service time at site *i*, s_i, is a random variable with known distribution function $f_1(s_1)$ that is independent of other service times.

The probability that site L_1 is visited is a function of travel time τ_{01}. Site L_2 is visited with probability

$$p(g_2 = 1) = p(a_2 \le H) = p(s_1 + \tau_{01} + \tau_{12} \le H) = p(\tau_{01} < H) \cdot \int_0^{H-\tau_{01}-\tau_{12}} f_1(s_1) ds_1 .$$

Similarly, site L_i is visited with probability

$$p(g_i = 1) = p(a_i \le H) = p(\tau_{01} < H) \cdot \int_0^{H-\tau_{01}-\tau_{12}} \ldots \int_0^{H-\sum_{j=1,\ldots,i} \tau_{j-1,j} - \sum_{j=0,\ldots,i-2} s_j} f_1(s_1) \ldots f_i(s_{i-1}) ds_1 \ldots ds_{i-1} .$$

Let $o \in O$ represent an individual outcome from the set O of all possible outcomes, where an outcome is defined as the state of completion of an *a priori* tour. Thus, each outcome $o \in O$ can be represented by $\{1, g_1, g_2, \ldots, g_n\}$. Let p_i be the probability associated with a given outcome $o \in O$, representing the probability that disaster sites $\{0, L_1, \ldots, L_i\}$ are visited and disaster sites $\{L_{i+1}, \ldots, L_n\}$ are unvisited. Thus, p_o is given by $p_i = \prod_{i=1,\ldots,n} p(a_i \le H)^{g_i} \cdot p(a_i > H)^{1-g_i}$. This computation assumes that a site is served if and only if the team arrives at the site before the end of the decision horizon *H*. For a given tour, the expected value of the number of sites that can be served is given by $E(L) = \sum_{i=1,\ldots,n} i p_i$.

The probability that site L_2 is visited in decision epoch t_i is given by

$$p(t_i \leq a_1 < t_{i+1}) = p\left(t_i \leq \sum_{i=1,2} \tau_{i-1,i} + s_1 < t_{i+1} \right) = \int_{t_i - \sum_{i=1,2} \tau_{i-1,i}}^{t_{i+1} - \sum_{i=1,2} \tau_{i-1,i}} f_1(s_1) ds_1 .$$

Similarly, the probability that site L_j is visited in the decision epoch t_i is given by

$$p(t_i \leq a_j < t_{i+1}) = \int_0^{t_{i+1} - \tau_{01}} \ldots \int_{t_{i-1} - \sum_{n=1,\ldots,j} \tau_{n-1,n} - \sum_{n=1,\ldots,j-2} s_n}^{t_{i+1} - \sum_{n=1,\ldots,j} \tau_{n-1,n} - \sum_{n=1,\ldots,j-2} s_n} f_1(s_1) \ldots f_i(s_{j-1}) ds_1 \ldots ds_{j-1} .$$

Consider the most general case in which the number of survivors at a site *i* at time a_i, $\tilde{D}_i(a_i)$, is a nonlinear, decreasing function of the team arrival time. Such a function can be approximated by a decreasing step function. Under this assumption, the expected reward associated with a given tour can be computed by

$$R = \sum_{i=1,\ldots,n} E\left(\tilde{D}_i(a_i)\right) = \sum_i \sum_j p(t_i \leq a_j < t_{i+1}) \cdot \tilde{D}_j(a_j).$$

The worst-case computational complexity required for evaluating the expected reward of an *a prior* tour, R, is $\mathrm{O}(2^{m \times n})$. Thus, the effort required for the computation of R, in the worst-case, increases exponentially with the number of decision epochs and number of sites included in a tour. Thus, it will be difficult to generate the expected reward of an *a prior* tour using analytical methods for large size networks.

An upper bound on R can be obtained by assuming that demand is a linear decreasing function of time. By this assumption,

$$R = \sum_{i=1,\ldots,n} E\left(\tilde{D}_i(a_i)\right) = \sum_{i=1,\ldots,n} \tilde{D}_i(E(a_i)).$$

If demand actually diminishes exponentially over time, then

$$R = \sum_{i=1,\ldots,n} E\left(\tilde{D}_i(a_i)\right) = \sum_i \sum_j p\left(a_j < H\right) \cdot \tilde{D}_j\left(a_j\right) \text{ and } \sum_{i=1,\ldots,n} E\left(\tilde{D}_i\left(a_i\right)\right) \geq \sum_{i=1,\ldots,n} \tilde{D}_i\left(E\left(a_i\right)\right).$$

It may also be beneficial to explore alternative approximations with reduced complexity. Schaefer et al. (2000) applied a Monte Carlo simulation method to estimate the expected cost of a round-trip itinerary for airline crew scheduling. Similar approaches can be also considered here.

5.4.3 The column generation-based approach

The number of feasible tours through one or more sites in need of assistance required as input to [SP$_i$] increases exponentially with increasing number of sites and number of scenarios. Thus, the computational effort required for direct and exact solution of [SP$_i$] for large problem instances may be very significant even for a single decision epoch. Moreover, a solution is required at each decision epoch. Recent works (Silva and Wood, 2006) have shown that column generation, a well-known integer programming solution method, is a viable approach for addressing two-stage stochastic programs. In the context of this work, such a methodology is found to be effective in reducing the number of tours that must be considered in solution of [SP$_i$] as compared with more traditional exact stochastic program solution techniques. And, while exhaustive in the worst-case, rarely is it necessary to consider all feasible tours.

To apply column generation in solution of a given instance of [SP$_i$], [SP$_i$] must be reformulated as a restricted master problem and sub-problem. The restricted master problem is formulated with only a subset of variables, or tours, of the original formulation. Inclusion of a variable, or tour, in the formulation results in the addition of a column if considered in a tableau format, where each column is associated with a decision variable (i.e. a possible tour). At each iteration of the column generation technique, the sub-problem is solved producing one or more additional columns with attractive reduced costs. These columns are added to the restricted master problem. This procedure iterates until no additional column can be added with negative reduced cost. In the worst-case, it is possible that every tour will be considered, i.e. every potential column will be added. However, in practice, it is often the case that the procedure will terminate having generated only a subset of feasible tours.

Thus far, solution by column generation of [SP$_i$] for only a single decision epoch has been considered. To solve the larger USAR-TDP, [SP$_i$] must be solved at each decision epoch. As solutions associated with consecutive decision epochs will be very similar, a column-generation-based technique using concepts posed by Chen and Xu (2006) for addressing a deterministic, but dynamic vehicle routing problem is proposed herein that exploits these similarities.

For a given decision epoch, t_i, and each team, $k \in K$, this technique generates a set of feasible tours over [t_i,H], given by $\bigcup_{k \in K} U_k(t_i) = U(t_i)$. Each tour serves a subset of the sites with known positive demand. The objective in updating the solution to the USAR-TDP for the current decision epoch is to determine the optimal combination of tours over select remaining sites. This solution will contain one tour for each starting location. Let $\Upsilon_{k\in K} U'_k(t_i) = U'(t_i)$ represent a limited set of feasible tours in [t_i,H]. The restricted master problem associated with [SP$_i$] for the USAR-TDP, denoted by [RMP$_i$], is given by replacing $U(t_i)$ with a subset $U'(t_i)$. The solution of the linear relaxation of [RMP$_i$] yields dual variables, which provide input to the sub-problem. Solution of the sub-problem then can be used to identify one or more new columns with favorable reduced costs or prove that no such column exists. The sub-problem for team *k* is given as follows.

$$Max \quad R_u + \sum_{w\in W} p_w \cdot \sum_{c\in C_u^W} r_{cu}^w y_{cu}^w - \sum_i \delta_{iu}^k \hat{\pi}_i - \hat{\mu}_k \tag{17}$$

Subject to

$$\sum_{u\in U_k(t_i)} \alpha_{iu}^w \cdot x_u^k + \sum_{u\in U_k(t_i)} \sum_{c\in C_u^w} \beta_{lcu}^w \cdot y_{cu}^w \le 1, \quad \forall i, w, \tag{18}$$

$$x_u^k - \sum_{c\in C_u^w} y_{cu}^w \ge 0, \quad \forall u \in U(t_i), \tag{19}$$

$$x_u^k, y_{cu}^w \in \{0,1\}, \quad \forall c \in C_u^w, u \in U(t_i), w \in W\ . \tag{20}$$

where $\hat{\pi}_i$ is an optimal dual variable associated with constraints (9) for each site *i* and $\hat{\mu}_k$ is an optimal dual variable associated with constraints (10) associated with each team *k*.

The reduced cost for any tour *u* is as following:

$$\begin{aligned}
\text{reduced cost} &= R_u + \sum_{w\in W} p_w \cdot \sum_{c\in C_u^W} r_{cu}^w y_{cu}^w - \sum_i \delta_{iu}^k \hat{\pi}_i - \hat{\mu}_k \\
&= \sum_{w\in W} p_w \cdot \left(\sum_i \delta_{iu}^k d_i(a_{iu}^w) + \sum_{c\in C_u^W} r_{cu}^w y_{cu}^w \right) - \sum_i \delta_{iu}^k \hat{\pi}_i - \hat{\mu}_k \\
&= \sum_{w\in W} p_w \cdot \left(\sum_i \delta_{iu}^k \left(d_i(a_{iu}^w) - \hat{\pi}_i \right) \right),
\end{aligned}$$

where $\hat{\pi}_0 = \hat{\mu}_k$. Let $\tilde{d}_i(a_i) = d_i(a_i) - \hat{\pi}_i$, representing the adjust reward of node *i*. Thus, the sub-problem seeks a tour for team *k* with the maximal expected adjust rewards given the tour length no greater than *H*. It is a NP-hard problem because its deterministic counterpart, the team orienteering problem, is shown to be NP-hard in Golden et al. (1987).

An exact column generation ends when the sub-problem cannot generate any column with positive reduced cost. If one or more new columns can be found with positive reduced costs, the current solution is nonoptimal and the corresponding tours must be added into the limited set of tours $U'(t_i)$ considered in [RMP$_i$]. [RMP$_i$] must be resolved with this updated set of tours. The process continues iteratively until no more columns with positive reduced cost can be found.

The proposed column generation technique employing such a local search heuristic is summarized as follows.

Column generation algorithm to solve problem [SP*i*]

Step 1: Generate an initial set of columns

For i=0:

Initialize [RMP$_0$] with a set of columns generated from solving the deterministic version of [SP$_0$] with mean value. All the tours generated are feasible in expectation.

For i≥1:

Begin with all columns used in the last iteration when solving [RMP$_{i-1}$]. For such columns, remove all the site that has been visited. Then, check whether or not the column is feasible in expectation. If the column is not feasible, remove the site one by one from the end of the column until it becomes feasible in expectation.

Step 2: Solve the linear relaxation of the restricted master problem [RMPi]

For all previously generated columns, solve the linear relaxation of [RMP$_i$]. Obtain optimal value $\bar{z}$ and dual solution (π, μ).

Step 3: Identify columns with positive reduced cost

Solve the pricing sub-problem to generate columns with positive reduced cost. The problem is NP-hard, thus, a local search heuristic is applied herein. A guided local search heuristic is performed as described in Vansteenwegen et al. (2009). Note that every column operated here is infeasible in expectation, but feasible in lower bound value of the service times. The sites are ranked according to their adjust rewards.

If any columns have negative reduced costs that exceed a given threshold, they can be eliminated from further consideration. If new columns are generated, add them to the [RMP$_i$] and return to step 2. Otherwise, terminate.

In typical USAR operations requiring response by government-sponsored USAR teams, service times at each site can be substantial and certainly greater than an hour. Thus, the number of sites included in construction of each column will be relatively small. Thus, columns can be generated quickly and a column generation-based approach can be computationally effective. The effectiveness of this approach is illustrated on an example problem in the next section.

5.5 Computational Experiments

The purpose of the numerical study is to demonstrate the feasibility of the proposed solution technique in quickly deploying USAR teams in the aftermath of a large-scale disaster. The solution approach is illustrated on a problem instance derived from data concerning structural failure following the 2010 earthquake in Port-au-Prince, Haiti. The test instance and parameter values are described in Section 5.5.1. In Section 5.5.2, implementation issues are discussed. This is followed by computational results that are presented in Section 5.5.3.

5.5.1 Problem instance setting and experimental design

On January 12, 2010, a 7.0-magnitude earthquake struck Port-au-Prince, the densely populated Haitian capital with more than two million residents. Untold numbers of people remained trapped under rubble following the disaster. Over 200,000 people perished and another roughly 300,000 were injured. Aid packages and organized USAR teams were rushed to Haiti immediately following the disaster from around the globe. The first USAR team arrived from Iceland in Port-au-Prince within 24 hours of the earthquake. By early afternoon, January 15, 1,067 foreign search and rescue workers searched for survivors with 114 dogs. Over the first weekend, there were nearly 2,000 search and rescue workers from 43 different organizations with 161 search dogs. Because of the overwhelming magnitude of damage to buildings and other civil infrastructure, it would take days to get help to all building sites in which survivors might have been in need of assistance. The search and rescue operations were called off on January 23. However, as late as February 8, survivors were still being found in the rubble. In total, more than 110 people were pulled from the rubble by USAR teams.

Figure 5-2 shows the damage assessment for major buildings and urban facilities in Port-au-Prince with a focus on hospitals, government and United Nations offices, schools, churches and industrial complexes. This map was generated by UNOSAT (The Union Nation Institute for Training and Research Operational Satellite Applications Programme). It should be noted that sites marked as "No Visible Damage" do not necessarily mean that such sites were not impacted by the earthquake. The damage levels were estimated based on visual interpretation of available satellite imagery and, thus, buildings with major structural damage, including building that may have collapsed, may not be identifiable. Damage, therefore, may be underestimated.

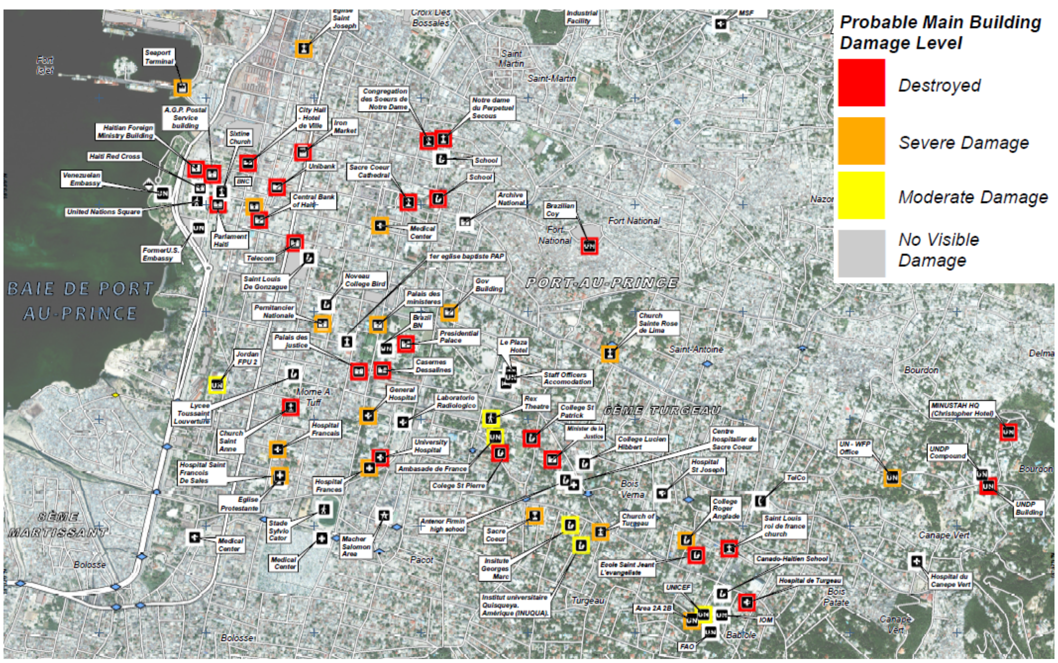


Figure 5-2 Damage assessment for major buildings/infrastructure in Port-au-Prince, Haiti

Immediately following the earthquake, UNOSAT identified 110 sites as the sites in most significant need of response. 58 sites of the 110 selected sites (i.e. 53% of the total), including 50% of the schools, 88% of the government-related buildings and 40%

of the hospitals, were visibly damaged or destroyed. Bridge and roadway conditions were quickly surveyed via satellite imaging and maps depicting damage were developed to aid in decision-making (UNOSAT, 2010).

The test instance developed herein was established using the 110 identified sites. The 58 sites with visible damage were assumed to be identified by time 0. Further, it was presumed that the remaining 52 identified sites were discovered over the decision horizon. These 110 sites are depicted in Figure 5-3. Depot is supposed to be Toussaint Louverture International Airport in Port-au-Prince, Haiti, located at the upper right corner of the map.

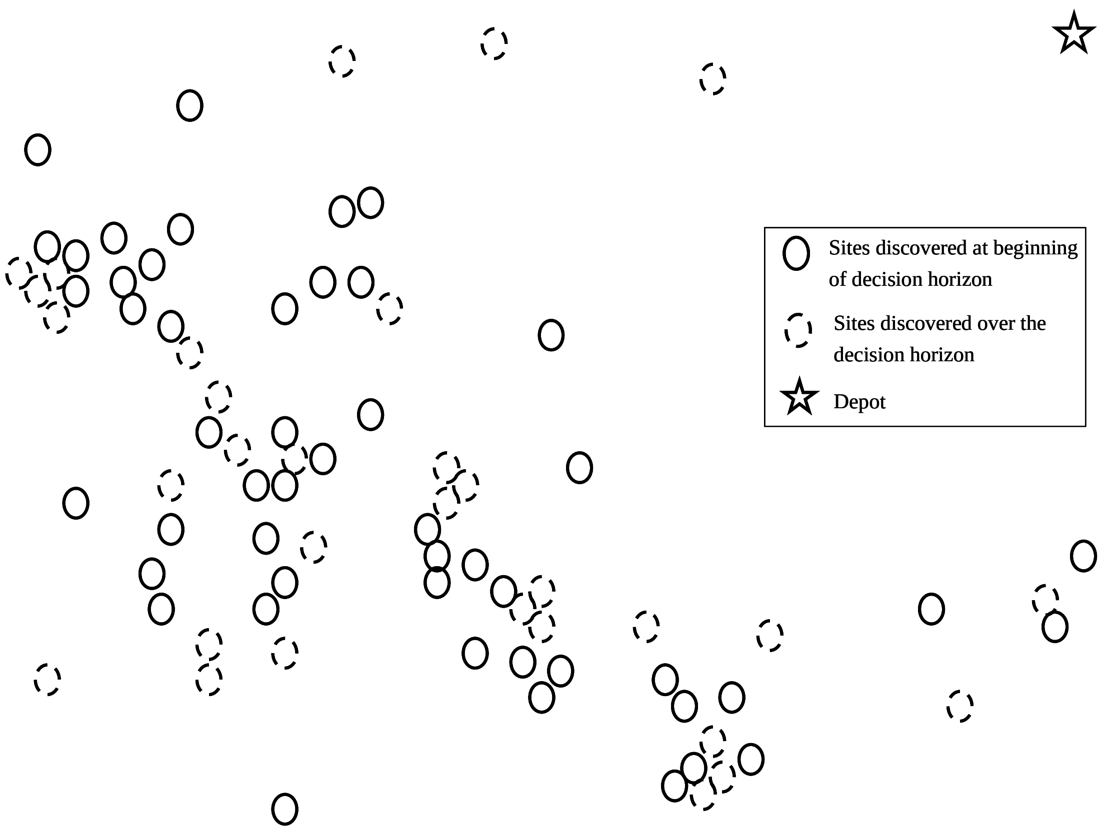


Figure 5-3 Disaster sites locations

Each decision epoch is set to be six hours in duration. Each team can work twelve hours per day. The decision horizon is set to five days, or ten decision epochs. USAR teams can consist of over 100 personnel. For example, the Virginia USAR Task Force, one of the FEMA task forces that responded to the Haitian event, consists of 131 members. Assuming 60 members per USAR team and given that many of the teams focused on sites of special interest, it is assumed that there are 15 USAR teams available over the decision horizon in total. Five of the teams were assumed to be available at the beginning of the decision horizon, five were assumed to arrive at the beginning of the second decision epoch, and the remaining five were presumed to arrive at the beginning of the fourth decision epoch.

The likelihood of finding survivors decreases with time. This likelihood depends on the building materials and survivors' physical conditions. The survival probability function from past earthquakes is summarized by Coburn et al. (1991). For simplicity, it is assumed that all 110 considered buildings were composed of weak brick or stone masonry. A discrete function is used herein to approximate the function developed by Coburn et al. This function is shown in Figure 5-4. The maximum time of surviving is set to be five days, consistent with estimates of four to seven day post-disaster survival periods (Coburn et al., 1991). The survival rate drops dramatically after the first three days. Alternatively, the survival rate can be approximated by an exponentially decreasing function $\tilde{D}_i(a_i) = \tilde{D}_{i0} e^{-0.375 a_i}$. Such a function would be convex. Thus, as noted previously in Subsection 5.4.2.2, $R = \sum_{i=1,\ldots,n} E\left(\tilde{D}_i(a_i)\right) \geq \sum_{i=1,\ldots,n} \tilde{D}_i\left(E(a_i)\right)$. Thus, $\sum_{i=1,\ldots,n} \tilde{D}_i\left(E(a_i)\right)$ provides a lower bound on the expected reward of an *a priori* tour. Such a bound can be exploited in the local search heuristic for generating attractive columns.

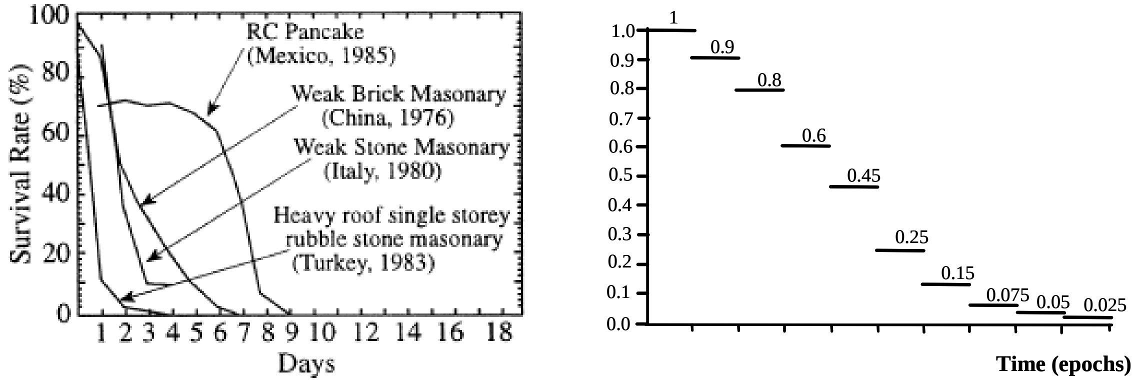


Figure 5-4 Real (left, taken from Coburn et. al, 1991) and approximated (right) survival rates

For simplicity, and due to a lack of data on pre- and post-earthquake roadway conditions, Euclidean distances over the plane are employed in estimating travel time. Thus, given the map scale of 1:15000 and the measured Euclidean distance between any two points in the space, travel times between sites can be calculated by the distance divided by a constant travel speed (assumed to be 40 miles/hour).

Three demand-related attributes are needed to generate the problem instance: estimated number of survivors at each site at the time the site is identified, the demand arrival process, and probability density functions of on-site service times. As it is difficult to acquire the additional data required to develop the problem instance, simulated data were generated from discrete uniform distributions for these factors based on limited real information. For example, if the site is known to be a moderately damaged school, the number of potential survivors might be quite high, while the number of potential survivors in a collapsed complex may be rather small.

Considering the different damage levels and uses associated with each building in

Figure 5-2, the number of survivors present upon site identification is generated from a uniform distribution ranging between 0 and a specific upper bound. The upper bound is calculated by the demand generation ratio, as given in Table 5-1, times 100. For demand arrivals, new demand sites were generated dynamically according to a Poisson distribution with parameter $\lambda = 100$. Then, the upper bound for the new demand will be determined by the product of the demand generation ratio given in Table 5-1 and the survival rate at the time that the site is identified. The size of the new demand, thus, will be generated from the uniform distribution between 0 and the upper bound.

Table 5-1 Parameters associated with survivor generation

Ratio	School	Hospital	Government -related	Other use of buildings
Destroyed	0.60	0.54	0.48	0.42
Severe damaged	0.80	0.72	0.64	0.56
Moderate damaged	1.00	0.90	0.80	0.70
No visible	0.50	0.45	0.40	0.35

The impacts of modeling stochasticity in service time on solution quality are explored through comparisons of various assumptions of service time distributions. Four such assumptions are enumerated next, creating four instances in the computational experiments.

1) All service times are independent and identically distributed random variables, following a discrete uniform distribution with $f(s;9) = 1/9, s = 6,...,14$;

2) For any site *i*, service time is uniformly distributed between $[l_i, u_i]$, where l_i is randomly generated from a discrete uniform distribution $f(l;5) = 1/5, l = 4,...,8$, and

$u_i = l_i + 8$.

3) The same as assumption 2, but l_i is not generated from a distribution. Instead, it is determined by $l_i = \left\lceil 6 \times \sqrt{\frac{\text{number of people at } i}{80}} \right\rceil$.

4) All service times are independent and identically distributed random variables, characterized by a truncated discrete normal distribution with $\mu = 0$ and $\sigma^2 = 5$.

The proposed algorithm and two other algorithms are used to solve the test instance for comparing the quality of the solution, i.e. the total expected rewards from all the visited sites. The other algorithms include a similar column generation-based approach in shrinking-horizons but based on solving the problem with mean values of the random variables, and a similar column generation-based approach in shrinking-horizons but based on solving two-stage stochastic models without recourse as shown in (16).

5.5.2 Implementation issues

Proposed solution techniques were implemented in Microsoft Visual Studio C++ 6.0 language with ILOG CPLEX callable library 9.1 (2005). Experiments were performed on a Windows XP personal computer with one 3.20 GHz CPU processor and 2.00 GB RAM.

The two-stage stochastic model, [SP$_i$], at the beginning of decision epoch t_i, can be easily constructed from [SP$_{i-1}$] by appropriately modifying the parameter values in the constraint matrix and coefficients within the objective function. Columns from the last iteration of solution in the previous decision epoch and related dual values serve as the initial set of columns and dual values for [SP$_i$]. These dual values are applied in computing reduced costs of the columns given updated information concerning demand arrivals and experienced service times. Columns with positive reduced cost will be considered for inclusion in the next iteration.

A branch-and-price method can be used in place of solving the linear relaxation [LSP$_i$] of the restricted master problem [RMP$_i$] when solution of [LSP$_i$] is non-integral. Based on findings from prior works (Johnson, 1989), if there is a fractional tour variable x_u, there must be a fractional variable $y_{jk}(t_i)$ which defines whether or not site j is visited by any team k in the solution of [SP$_i$]. Thus, instead of branching on the tour variable x_u, it is more efficient to branch on $y_{jk}(t_i)$. Branch-and-price scheme guarantees optimality. However, it is often the case that exact solutions are not necessary. Near optimal solutions with fast computational times are sufficient. An alternative is to solve the [RMP$_i$] directly with the MIP solver in CPLEX, despite that by such direct solution, a column with positive reduced cost may not be in [RMP$_i$] currently. Thus, this implementation does not guarantee optimality.

5.5.3 Computational results

The test instance contains ten stages, resulting in ten interrelated two-stage stochastic programs. Table 5-2 provides the computational performance associated with solution of the program at each stage.

Table 5-2 Computational performance of two-stage stochastic programs

Stage	Problem size			Solution time (seconds)	# of columns
	# of teams	# of sites	Remaining time (hours)		
1	5	58	60	453.5	7905
2	10	59	54	380.5	7925
3	10	62	48	244.5	8120
4	15	66	42	187.5	5900
5	15	70	36	70	4465
6	15	75	30	69.5	3965
7	15	80	24	46.5	1720
8	15	84	18	56	2332
9	15	87	12	94	599
10	15	88	6	56.5	443

As shown in Table 5-2, the performance of the proposed column generation-based approach improves nonlinearly with each stage, as fewer sites remain for possible inclusion and remaining time for action decreases. The approach is shown to be very effective in addressing the USAR-TDP problem instance of Haiti. Such problems are amenable to solution by this approach, because of the relatively large on-site service times. Initial tours contain few sites and recourse actions involve the addition of only one or two sites to any tour in most cases.

Table 5-3 provides the computational results for the test instance with different service time distributions. Three different modeling techniques are considered within the dynamic solution framework: deterministic (D); stochastic, but no recourse (SSP, Subsection 5.4.2.1); and stochastic with simple recourse (SP, Subsection 5.4.2.1). In the first approach, random variables are replaced by their mean values, creating a deterministic version of the problem. In the second approach, the SSP described in

Subsection 5.4.2.1 is solved. Finally, in the last approach the SP is solved directly. Four service time distributions are considered, as described in Section 5.5.1.

Table 5-3 Computational performance of two-stage stochastic programs

Service time distribution	Objective function		
	Deterministic	Stochastic without recourse	Stochastic with simple recourse
Distribution (1)	1294	1616	1650
Distribution (2)	1307	1537	1649
Distribution (3)	1388	1594	1738
Distribution (4)	1294	1470	1472

Results of these experiments indicate that the values of modeling stochasticity and permitting recourse actions are significant. On average, the objective function value improved by 23.2% between (D) and (SP), indicating that stochastic factors may significantly affect the optimality of the problem. Additionally, on average, the objective function value improved by 4.6% between (SPP) and (SP), showing that incorporating team interactions can result in improved solutions.

5.6 Conclusions and Extensions

In this work, the USAR-TDP for addressing the need to quickly respond to disaster to mitigate its negative impacts is conceptualized. The problem seeks to identify a set of non-overlapping tours for USAR teams so as to maximize the total expected number of people that can be saved by attending to all or a subset of disaster sites within the disaster region. To address the probabilistic and dynamic nature of conditions following a disaster, the on-site service times are assumed to be known only with uncertainty and sites requiring assistance arrive dynamically over the decision horizon. A multistage stochastic, integer program is formulated to model the sequential stochastic information process. To overcome the expensive computational effort associated with the solution of a multistage stochastic program, a column generation-based strategy that consists of solving a series of interrelated two-stage stochastic programs with recourse within a shrinking-horizon framework is developed. Two types of recourse are considered and set-partitioning-type formulations for both are developed. Consistent with information availability in disaster applications, the algorithm relies only on information available at each decision epoch.

Experimental results from a test case developed to replicate events of the 2010 Haiti earthquake illustrate the feasibility and efficiency of applying the proposed solution technique in support of USAR operations in real-world applications. Moreover, the value of considering stochasticity in on-site service times is shown to be significant.

In post-disaster scenarios, conditions change rapidly with time. USAR strategies must adapt to ground realities, including new information from reconnaissance efforts, new resources, and progress made by deployed teams. This work addresses this by developing tools for robust decision support. For example, a particular site may require more time than anticipated, depriving potential survivors at other sites. In light of such information, routing and resource allocation decisions made previously must be quickly evaluated to see if improved strategies or reprioritization is required. Such real-time decisions must be made quickly and USAR teams must be immediately informed of their new tasks. In this study, uncertain service times and the dynamic arrivals of new demands are considered. Models and solution techniques to address other uncertainties, e.g. roadway conditions, will be a future research direction.

This research will provide logistical support to incident commanders charged with deploying USAR teams in the event of a large-scale disaster, where victims have become trapped in collapsed buildings or in flooded streets and are in immediate need of rescue. By explicitly considering the inherent stochastic and dynamic nature of the hazard conditions, and potential location of survivors in need of assistance, and by further employing real-time communications from the on-site USAR personnel and reconnaissance teams in updating the routing of teams and allocation of resources to sites in on-line operations, the resulting decisions can aid USAR teams in expeditiously locating and extricating survivors, and thus, saving more lives. The proposed methodologies can be used off-line for a posteriori analyses to assess decisions that were taken in-situ. These tools can be used to obtain exact, updated solutions, providing benchmark solutions for development of heuristics or simple protocols for USAR personnel deployment and resource allocation that can be used on-line to provide real-time decision support. The potential impact of decisions resulting from the tools developed in this work on equity, fairness and other ethical concerns will need further investigation.

This research effort is a first step in bringing state-of-the-art optimization techniques – similar to those already in use by private enterprises for other applications – to aid USAR operations. Few works have addressed the optimization of USAR operations or related problems and none of these has considered the probabilistic and dynamic nature of conditions surrounding a disaster. Traditional optimization techniques that may have utility in this context cannot address the complexities of USAR operations or conditions in which USAR teams work. Consequently, existing procedures will likely result in suboptimal decisions. If the dynamic and uncertain nature of conditions present in such situations is considered and real-time updates to this information are employed, more efficient operations will result. The procedural steps for identifying optimal decisions for USAR operations in such dynamically changing environments will permit the identification of robust solution strategies in solving problems of a scale seen in real-world applications. These improved solutions will result in greater payoff in exchange for the risk endured by the rescuers. A decision support tool that takes into account society's need for safety in the case of disaster or terrorism resulting in region-wide destruction increases the public's faith in the government entities responsible for USAR.

Emergent groups of volunteers who immediately respond post-impact of a disaster to help with reconnaissance and rescue, disaster relief, medical aid, transport and other key emergency response functions are a critical component of any community's emergency response capability. In the immediate aftermath of a disaster, the local community is isolated and must rely on locally available resources (Noji, 1997). It may take many hours for state and national emergency response organizations to arrive on location once the acute need for external assistance is recognized and a request for their help is made. Thus, every community must have the capability and capacity to help itself (Noji, 1997; Barton, 1969) at least in the immediate term. Since a significant portion of the victims require medical aid in the first hours after the disaster impact(Noji, 1997; Noji, 1989), these volunteers and local agencies must be the first line of response. Many works in the literature describe events where the majority (even as high a 90 or 95%) of survivors who were rescued, were saved by unskilled, untrained volunteers and other uninjured survivors (Barton, 1969; Noji, 1989; Wenger, 1991; Noji 1997; Tierney et al., 2001). In some documented disasters, by the time the special forces arrived on site, only technical rescues, requiring special training and equipment necessary for disassembling collapsed structures and extricating trapped victims, remained (Noji, 1989; Poteyeva, 2007). Since such technical rescues require enormous human-power and can take hours each (Noji, 1989), it is critical that these special teams spend the majority of their effort on the more difficult technical rescues requiring special skills and equipment that ordinary and even relatively well trained civilians could not assist with. In events where the victims outnumbered the volunteers, as in the aftermath of Hiroshima (Barton, 1969), the death tolls were enormous. Undoubtedly, the mass assault and emergence of groups or multi-organizational networks that are described and conceptualized in, for example, (Drabek et al., 1981; Drabek, 1983; Kreps and Bosworth, 1993; Ross, 1980; Wenger and Thomas, 1994; Stallings and Quarantelli, 1985; Quarantelli et al., 1977) are required for a community's response to disaster. The proposed formulation and solution technique do not diminish the role of the volunteers and emergent groups in disaster response.

While every community should be prepared, a centralized process, as could be provided by the federal government, is appropriate for serving certain emergency response functions, where local, decentralized systems fail. It would be inefficient for every local community to independently develop emergency response capabilities for all conceivable disasters (Drabek, 1985). This work aids in mobilizing the specially trained task forces and could be extended to aid in deploying groups of volunteers, should a community be well organized enough to make effective use of its volunteers. Consequently, results of this effort can aid in mitigating some of the difficulties that arise in coordinating USAR activities (as described in, for example, Poteyeva et al., 2007).

Chapter 6 Conclusions and Extensions

6.1 Conclusions

In this dissertation, three important optimization problems associated with evacuation, transportation network vulnerability and emergency response are considered in time-dependent, stochastic and/or dynamic environments. This dissertation is motivated by the increasing need to better secure the transportation system and better prepare for unexpected events, thus, mitigating loss due to emergency occurrences. Despite its importance and practical applications, it does not appear that any of the problems proposed and solved herein has been previously conceived in the literature.

This dissertation addresses three problems: the building evacuation problem with shared information (BEPSI), the network resilience problem (NRP) and the urban search and rescue teams deployment problem (USAR-TDP). These models can aid in decision-making during pre-disaster preparedness and post-disaster response, as discussed in Chapters 3 through 5. The focus of this dissertation is to conceptualize, formulate and provide algorithmic approaches (exact and approximate) to tackle these problems.

In addition to the mathematical and methodological contributions associated with strategies for evacuation, response and recovery, an exposition of security concerns associated with transportation systems, including the role of transportation in emergency management and in supporting other critical lifelines, as well as the transportation network as the target of natural or terrorist attack, is provided. This focused discussion provides a viewpoint for considering how the issues tackled within this dissertation fit within the larger concerns of security and the movement of people, critical resources and supplies.

The BEPSI is formulated as a mixed-integer program and is solved by an exact algorithm based on Benders decomposition. The NRP is formulated as a stochastic program with only second-stage variables and is solved by a solution technique composed of Monte Carlo simulation, Benders decomposition and column generation. The USAR-TDP is formulated as a multistage stochastic program and an approximation method involving exact solution of a sequence of interrelated two-stage stochastic program with recourse is developed. The formulations proposed in this dissertation provide precise problem definitions and permit quantitative analyses of real-world problem instances. The problems are either shown to be NP-hard or are stochastic and/or dynamic, and thus, are known to be difficult problems.

Computational experiments were conducted on network representations of an actual multi-story building, a double-stack container network representing the Western United States and building failure following the Haitian earthquake. Results of these experiments illustrate the potential of applying the proposed procedures to realistic-size problems. The results show that these exact and approximation algorithms can solve small- and moderate-size problems to optimality or near optimality with reasonable computational time for off-line use and demonstrate the feasibility of their applications. The solution techniques developed in this dissertation can provide a mechanism for developing exact solutions to these difficult problems. While none were designed to be fast enough for on-line use, where applicable, simpler heuristics can be developed that will support decision-makers faced with difficult, urgent decisions arising in emergency preparedness planning and post-disaster response. The quality of the solutions created by such heuristics can be assessed through comparison to exact solutions from the techniques provided herein.

6.2 Extensions

The BEPSI

The problem is formulated as a mixed-integer linear program. It is proven to be NP-hard and is solved exactly by a Benders decomposition method. Although the solution technique is shown to be effective in solving a mid-size, real-world problem, heuristics could be developed to more quickly obtain feasible and, hopefully, near-optimal solutions for large buildings for on-line applications where instructions would be provided to evacuees during the evacuation. The procedures developed for this problem may have utility in other functional areas as well, such as, for example, evacuation of a geographic region where evacuation instructions can be provided to vehicles via changeable message signs, radio, the internet, or other advanced Intelligent Transportation Systems technologies.

The NRP

A quantitative, system-level indicator of network recovery capability is proposed in Chapter 4 for the NRP and the problem is formulated as a stochastic program. Even considering only one possible network state, the NPR is shown to be NP-hard. An exact procedure over a set of network states for each disaster scenario is proposed and network states are approximated by Monte Carlo simulation. Heuristics may be required to compute the resilience of large networks. One might also consider modifying the objective function to incorporate the priority of demand between O-D pairs. Such consideration is especially useful in the situation of a disaster when emergency resources need to be sent to the disaster zone as quickly as possible. The stochastic program developed in this study contains no first-stage variable because actions will be reactive and are taken in the aftermath of disaster. It may be beneficial to incorporate preparedness actions, i.e. proactive measures, prior to disaster occurrence, if these actions are cost effective and considerably improve the system's capability to cope with disaster. The stochastic program proposed herein can be extended for this purpose to include first-stage variables representing actions taken before disaster scenarios are revealed. It is also expected that the proposed resilience concept can be applied more widely to other networks systems, e.g. computer systems, as a quantitative measure of system vulnerability.

The USAR-TDP

The USAR-TDP is formulated as a multistage stochastic program, capturing the probabilistic and dynamic nature of conditions immediately following a disaster. An approximate solution technique is proposed to solve a series of two-stage stochastic programs with recourse. A future extension may consider designing an algorithm to directly solve the multistage stochastic program by approximating the recourse functions between stages. Circumstances immediately following a disaster are highly uncertain and dynamic. The environment may be hostile due to ongoing events, such as aftershocks following an earthquake. While stochastic service times and dynamically arising demand are considered in this work. Uncertainty in, for example, stochastic travel time and number of people in need of assistance at each site might also be considered. Moreover, correlation between demand and on-site service time can be explicitly considered. In this work, the arrivals of USAR teams in the disaster region is modeled, however, it is assumed that teams' arrival times are known at the start of USAR operations. Uncertainty in USAR team arrival might be explored in future studies. Instead of maximizing the expected number of people that can be saved, one can consider the objective of maximizing the probability that the number of people saved is greater than a given threshold. Detailed design of a decision support system (DSS) in which USAR-TDP solution techniques, or faster heuristics, would be embedded to provide decision support for the incident commander in charge of the disaster response is also an interesting area of future research.

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