MODELING EVACUATION TRAFFIC IN DEGRADABLE TRANSPORTATION SYSTEMS

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ABSTRACT OF THE DISSERTATION

Modeling Evacuation Traffic in Degradable Transportation Systems

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Transportation systems are at the epicenter of attention when a disaster happens due to their importance in evacuating victims in the pre-disaster phase, as well as providing supplies to the survivors in the aftermath of any major disaster. When disasters happen, transportation systems are degraded by either exogenous risks, such as flooding or earthquake, or endogenous risks, such as accidents and disabled vehicles. Modeling evacuation traffic in degradable transportation networks is thus critical for public officials in developing effective hazard mitigation plans.

Over the past decade, a number of emergency evacuation models have been developed. However, these models are generally developed for so-called "expected" conditions (e.g., clear weather and few accidents) without considering disruptions in transportation systems. Moreover, these models were originally developed for different

emergency scenarios with specific algorithms and software tools, which limit specialized analysis of emergency scenarios.

This dissertation aims to provide a new framework and methodology to model evacuation traffic by extending the use of existing regional transportation planning tools. In order to capture the occurrence of congestion during the evacuation process, a pseudo-dynamic procedure is developed and employed. Moreover, in order to evaluate evacuation planning considering the transportation system variability (e.g., incidents, accidents, and extreme weather conditions), we propose an analytical methodology and solution procedure that employs a sampling technique that randomly selects subsets of the uncertainty set to obtain an approximate solution.

The proposed analytical framework and solution procedure are applied to evaluate critical transportation infrastructures in day-to-day degradable transportation networks. Moreover, we also apply the proposed analytical framework and solution procedure to evaluate the impact of endogenously determined risks in order to develop reliable emergency evacuation plans. In addition to evacuation modeling, recently Hurricane Irene (2011) made landfall in New Jersey. We have a special chapter that analyzes the empirical evacuation behavior and constructs an evacuation response curve based on traffic data collected during Hurricane Irene (2011) in Cape May County, New Jersey.

Dedication

To my parents Liuzheng Li and Ying Wang

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Preface

This dissertation is based on the following studies.

Projects

- Modeling disaster operations from an interdisciplinary perspective in the New York / New Jersey area. Funded by Region II University Transportation Center.
- Development of a statewide transportation evacuation planning model in New Jersey. Funded by U.S. Department of Homeland Security.
- Urban Area Security Initiative (UASI) regional evacuation plan for north New Jersey Phase I, Phase II. Funded by U.S. Department of Homeland Security.

Papers

- Li, J., K. Ozbay, B. Bartin, S. Iyer, and J. A. Carnegie. (2013). Hurricane Irene empirical evacuation response curve in Cape May County, New Jersey. *Journal of Transportation Research Record*, in press.
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- Ozbay, K., J. Li, M. A. Yazici, S. Iyer, E. E. Ozguven, and J. A. Carnegie. (2012). Pseudo-dynamic evacuation modeling procedure. The Second International Conference on Evacuation Modeling and Management, Chicago, IL, USA, August 13–15.
- Li, J., and K. Ozbay. (2012). A cell-based stochastic dynamic traffic assignment model and solution procedure to capture endogenous network degradation risks during evacuations. The 4th International Symposium on Dynamic Traffic Assignment, Martha's Vineyard, MA, USA, June 4–6.
- Li, J., and K. Ozbay. (2010). An investigation of the convergence and accuracy properties of Latin hypercube sampling technique for traffic equilibrium problem under capacity uncertainty. Proceeding of 89th Annual Meeting of Transportation Research Board, Washington, DC, USA, January 10–14.

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1 INTRODUCTION

1.1 Background

Evacuation problems have drawn significant interest in the transportation field since the last half century. As early as World War II and later in the Cold War era, evacuation was introduced in order to save the civilians, particularly children, by moving them out of urban or military areas where they could become targets. More recently, with the development of satellite technology in 1960s and 1970s, planners began to pay attention to the evacuation of coastal areas before the landing of hurricanes. Later, after the Three Mile Island incident in 1970, the attention in the field of evacuation planning has switched to nuclear power plants. Recently, emergency evacuation has drawn significant interest due to the increasing risk of man-made and natural disasters, such as the September 11 attacks, Hurricane Katrina, and recently Hurricane Sandy. A detailed review of evacuation problems in the transportation field can be seen in Wolshon (2008).

The main objective of evacuation planning is to ensure the safety and most efficient evacuation time of all expected residents of a structure, city, or region. There are several key technical components in an emergency evacuation plan. Baker (2001) summarized the key technical and policy components for hurricane evacuation planning (see below), and the general process can be applied to any other hazards.

- Hazard analysis: identify the area that would need to be evacuated for a particular hazard condition.
- Vulnerability analysis: ascertain the number of households and people who are susceptible to the threat condition.
- Behavioral analysis: project how people will respond to the threat.

- Transportation analysis: assess roadway capacities within the transportation network and identify conditions such as bottlenecks or links vulnerable to the hazard. The objective of the transportation analysis is to develop clearance time within an evacuation area. Clearance times are estimates of the time that would be required to evacuate an area.
- Shelter analysis: evaluate the capability of buildings to withstand the hazardous conditions and their suitability to be used as refuges for evacuees.
- Decision making: develop procedures to assess whether a hazard presents a level threat to warrant an evacuation and, if so, when to initiate an evacuation order.
- Development management: regulate the growth of the population and land development that could make evacuation more difficult.

Transportation systems are at the epicenter of attention when disasters happen due to their importance in evacuating victims in the pre-disaster phase, as well as providing supplies to the survivors in the aftermath of these disasters. When disasters happen, transportation infrastructure, especially potential bottlenecks such as bridges and tunnels, is critical for emergency response and operations. The loss of such transportation infrastructure would significantly delay the evacuation process in the pre-disaster phase. It was observed during Hurricane Rita evacuation (Litman 2006) that “an estimated three million people evacuated the Texas coast, creating colossal 100-mile long traffic jams that left many stranded and out of fuel; inefficient use of road capacity and the effects of ill-planned evacuation, resulting in disorganized movement of people.”

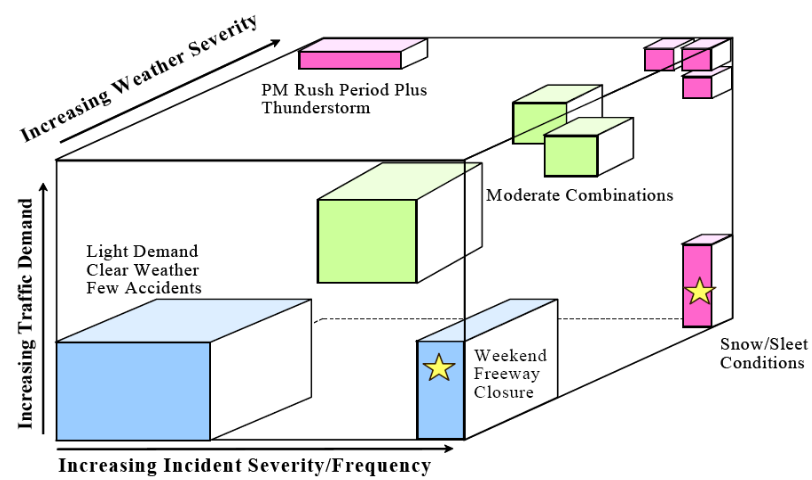
1.2 Motivation

Evacuation clearance time is the key performance measure in transportation analysis. The time may vary greatly depending on several factors, including the total number of people in the affected area, the conditions of evacuation routes, the evacuees' response behavior, the availability of shelters nearby, and the nature of the emergency itself. Because of the dynamic nature of evacuation process, computer-based simulation models are common tools to estimate evacuation clearance times.

When modeling evacuation traffic in computer-based simulation models, roadway capacity is critical for handling high volumes of evacuation demand without experiencing severe congestion. In order to increase the roadway capacity, there are some evacuation traffic management solutions, such as reversible flow, suspension of tolls, adjustment of signal timings, and so on. However, unfortunately, many possible uncertain events may also reduce roadway capacity and slow the evacuation process. Such uncertain events including severe weather, traffic incidents/accidents, and poor infrastructure maintenance may cause loss or partial blockage of certain roadways that are heavily traveled. In addition, because of high volume of evacuation traffic and stress-driven behavior, uncertain events such as traffic accidents or disabled vehicles are more prone to happen and cause significant delays.

Capturing uncertainty in transportation system evaluation is important for arriving at better planning decisions, especially under emergency situations that are typically characterized by uncertainties. Traditional evaluation of network capacity conducted for so-called "expected" conditions assumes that the routes are going to operate under almost ideal conditions such as light demand, clear weather, and few accidents (see FIGURE

1-1). Obviously, the potential road capacity uncertainty requires comprehensive transportation planning, which not only includes "expected" conditions but also pays attention to scenarios where uncertain events happen. Under uncertainty, instead of a single value, a probability measure (e.g., transportation system costs) is much more appropriate for evaluation of the robustness and performance of a road network. Moreover, transportation infrastructure also needs comprehensive performance, which not only concerns the levels at which the item is designed and built but also reflects the operational-related issues that are influenced by the item's potential to remain operational and the ease with which the item is repaired, maintained, and returned to operation.



Source: Wunderlich, K., et al., *Seattle 2020 Case Study*, PRUEVIIN Methodology, Mitretek Systems. This document is available at the Federal Highway Administration Electronic Data Library (http://www.itsdocs.fhwa.dot.gov/).

FIGURE 1-1 Multiple Conditions in Transportation Systems

Thus, it is essential to construct a new tool that can assist researchers or policy makers in comprehensively evaluating the transportation system by incorporating realistic traffic operation conditions. Instead of a traditional planning approach with average or ideal network supply conditions, the proposed new approach takes into account realistic conditions for evaluating transportation system performance under emergency situations. This network evaluation is based on more realistic transportation facilities monitoring, uncertain events detection, and evaluation of the potential influence. Moreover, the comprehensive realistic transportation facilities evaluation and short-term improvement strategies can also provide feedback for the evacuation planning process and benefit its flexibility and responsibility in scale (level of detail) and scope (alternatives and impacts considered).

1.3 Problem Statement

This dissertation aims to provide a framework and methodology to model evacuation traffic by using existing regional transportation planning tools. Regional demand models are available in many regions and have been well calibrated for the area. In order to capture the potential congestion during the evacuation process, a pseudo-dynamic procedure is developed and employed. The logic of the pseudo-dynamic procedure is based on running consecutive traffic assignments with short time intervals and updating the traffic based on how much of the existing traffic will stay as residual traffic during the following assignment period. If the scenario specifications allow for the use of an existing general-use transportation planning model, the proposed methodology can be used for customizing the selected tool to make inferences for the scenario-related case studies.

In order to evaluate evacuation planning considering the system variability, such as the impacts of uncertain events (e.g., incidents, accidents, and extreme weather conditions), we propose an analytical methodology and solution procedure by using a sampling technique that randomly selects subsets of the uncertainty set to obtain approximate solutions. Sample Average Approximation (SAA) is employed to generate plausible realizations of network degradation conditions and solve the stochastic programming. Moreover, Latin Hypercube Sampling (LHS) was used in order to obtain an efficient sample size for the SAA methodology. We applied the proposed analytical methodology and solution procedure to solve two types of problems.

- Critical infrastructure evaluation and protection. This is an important problem for public officials to make hazard mitigation planning. We applied the proposed analytical framework and solution procedure for link criticality evaluation, which considers the impact of day-to-day degradable transportation network conditions.
- Modeling evacuation traffic in degradable transportation networks. This is an important issue for public officials to avoid unexpected delays and related losses of life and property. We applied the proposed analytical framework and solution procedure to evaluate the impact of endogenously determined risks in order to develop reliable emergency evacuation plans.

In addition to evacuation modeling, behavior analysis is another critical issue for public officials in deciding when to issue emergency evacuation orders. Such behavior is typically measured by an evacuation response curve that represents the proportion of total evacuation demand over time during evacuation. We have a special chapter to analyze evacuation behavior and construct an evacuation response curve based on traffic data collected during Hurricane Irene (2011) in Cape May County, New Jersey. The evacuation behavior analysis and calibrated evacuation response models based on this recent hurricane evacuation event may benefit evacuation planning in similar areas.

1.4 Thesis Outline

In this dissertation, an analytical methodology and solution procedure are proposed for modeling evacuation traffic in degradable transportation systems.

Chapter 2 reviews emergency planning and transportation models, as well as risk analysis for degradable transportation networks in particular to provide a context for the proposed evacuation traffic modeling platform.

Chapter 3 presents an evacuation modeling framework by utilizing widely available regional transportation planning tools. The proposed procedure is tested with a case study using a developed regional travel demand model.

Chapter 4 proposes an analytical methodology and efficient solution procedure to evaluate evacuation planning considering the system variability, such as the impact of uncertain events (e.g., incidents and extreme weather).

Chapter 5 is an application of proposed methodology in chapters 3 and 4 by using the sampling solution approach to determine and rank critical links. Chapter 6 is an extension of the analysis approach provided in chapters 3 and 4 by evaluating the impact of endogenously determined risks in order to develop reliable emergency evacuation plans.

Chapter 7 is a special study of empirical evacuation response curve during Hurricane Irene in Cape May County, New Jersey.

Chapter 8 summarizes the conclusions and proposes future research.

2 LITERATURE REVIEW

This chapter provides an overview of emergency planning and transportation models, as well as risk analysis for degradable transportation networks in particular to provide a context for the proposed evacuation traffic modeling platform.

2.1 Transportation Planning for Evacuation

For decades we have focused on transportation planning with traditional criteria including accessibility, mobility, environment, safety, and so forth. The objective of traditional transportation planning is to reduce the system costs by improving efficiency. However, with the increasing frequency of hazard events, such objectives need to be revised by considering the requirements of transportation security, which focus on analyzing the vulnerability of transportation systems to natural or man-made disasters.

2.1.1 Traditional Transportation Planning

Transportation, in Chinese philosophy, means connection and exchange. Transportation systems firstly connect and provide proper accessibility to certain places; then people and goods gather together to exchange to satisfy basic human requirements for dwelling, work, and recreation. The performance of transportation systems widely affects every aspect of human society. Therefore, planning for the development or maintenance of the urban transportation system is an important activity, both for promoting the efficient movement of people and goods in a metropolitan area and for providing a strong supportive role in attaining other community objectives.

Transportation planning is a cooperative process designed to foster involvement by all users of the system, such as the business community, community groups, environmental organizations, the traveling public, freight operators, and the general public, through a proactive public participation process conducted by the Metropolitan Planning Organization (MPO), the state Department of Transportation (DOT), and transit operators. According to the summary by the Federal Highway Administration (FHA) and Federal Transit Administration (FTA), transportation planning includes a number of steps (FHA and FTA 2007):

- Monitoring existing conditions
- Forecasting future population and employment growth, including assessing projected land uses in the region and identifying major growth corridors
- Identifying current and projected future transportation problems and needs and analyzing, through detailed planning studies, various transportation improvement strategies to address those needs
- Developing long-range plans and short-range programs of alternative capital improvement and operational strategies for moving people and goods
- Estimating the impact of recommended future improvements to the transportation system on environmental features, including air quality
- Developing a financial plan for securing sufficient revenues to cover the costs of implementing strategies

However, experiences with the terrorist attacks of September 11, 2001, and Hurricane Katrina and Rita have demonstrated that the traditional transportation planning, design, and management processes that work well under normal conditions are not adequate in responding to the needs of emergency evacuations. Recent experience in evacuating populations during Katrina and Rita demonstrates a lack of adequate preparation for emergencies and points to the need for improving the planning and design of transportation systems for meeting the transportation needs of the population to be evacuated from dangerous areas to safe areas during an emergency. Recent experience also indicates a need for achieving better coordination between first-responder agencies and between different political jurisdictions. There is little doubt that transportation agencies need to reexamine their mission statements with the objective of making emergency evacuation planning an integral part of their work programs.

2.1.2 Evacuation Events

Emergency evacuation is the mass physical movement of people away from a threat or the actual occurrence of a hazard. Such hazard events can be associated with a board range of affected scale. Examples range from the small-scale building evacuation due to a fire to the large-scale regional evacuation because of a hurricane. Wolshon (2005) grouped evacuation events into two categories: natural evacuation events and man-made evacuation events.

2.1.2.1 Natural Evacuation Events

Natural evacuation events are threats of naturally occurring events that will have negative effects on people or the environment. A database maintained by the Federal Emergency Management Agency (FEMA) reports the number of U.S. State/Tribal-declared disasters. FIGURE 2-1 shows historical data from the FEMA database by type of disaster for the years 1953 through 2012. Natural evacuation events in the United States deal with seven broad classes: flood, severe storm, fire, wildfire, tornado, hurricane / tropical storm, and winter storm. Flood and severe storm are the two major disasters and account for 24.2% and 22.6%, followed by fire (13.3%), wildfire (12.2%), tornado (8.1%), hurricane / tropical storm (6.9%), and winter storm (6.3%) in third to seventh place, respectively.

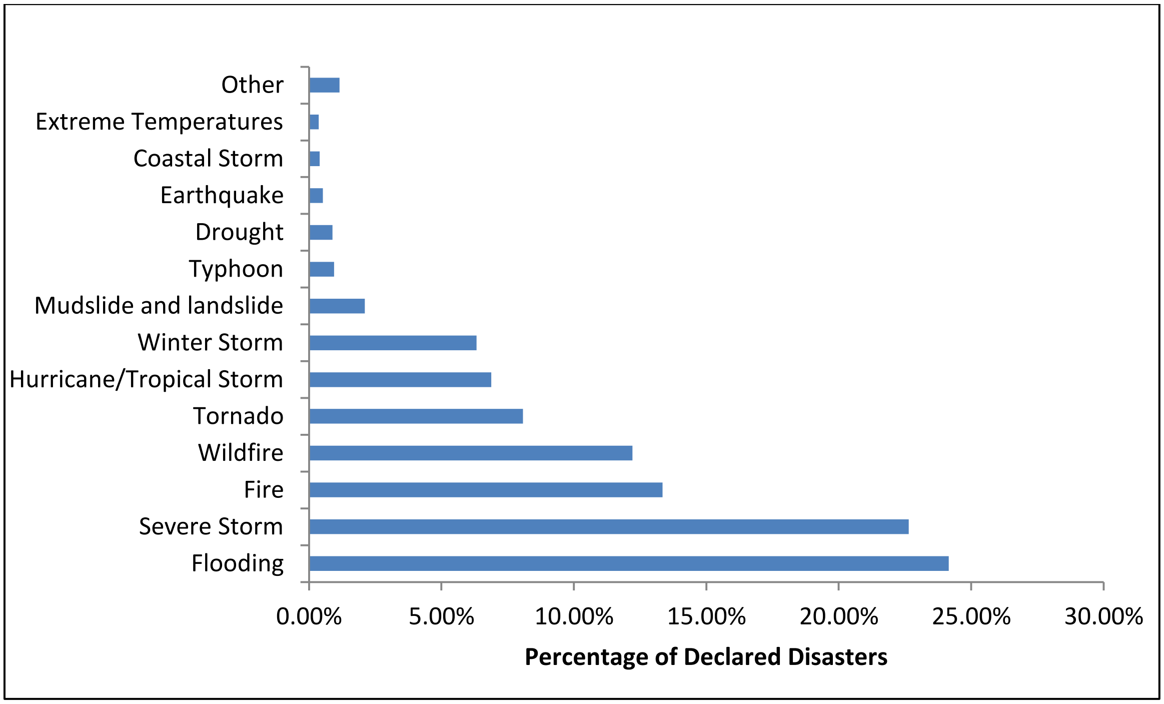


FIGURE 2-1 Declared Disasters by State/Tribal Government, 1953–2012.

(Source: Federal Emergency Management Agency, http://www.fema.gov/disasters)

Another useful distinction between natural evacuation events is being able to provide advance notice or not. The main difference is the amount of warning that precedes the evacuation-inducing event. With no-notice events, there is no warning. Evacuation from no-notice events often occurs nearly immediately after an event has occurred. Advanced-notice events are preceded by some amount of warning, which may be only a short amount of time. The normal amount of warning for these events is 24–72 hours. Advanced-notice events, such as hurricanes, can be deterred by visual cues or technology, such as weather satellites. Advanced-notice evacuations can also occur if there is a time lag between the event occurrence and the threat to the population.

At last, it should be noted that many natural hazard events are interrelated. A recent example is the 2011 Tohoku earthquake. The 9.0-magnitude undersea earthquake occurred on March 11, 2011 in the northwestern Pacific Ocean. Later, the earthquake resulted in a major tsunami that brought destruction along the Pacific coastline of Japan's northern islands. The aftermath of the earthquake and tsunami included both a humanitarian crisis and a major economic impact.

2.1.2.2 Man-Made Evacuation Events

Man-made evacuation events were grouped by Hardy and Wunderlich (2007) into six broad classes: special event, technological, hazardous material, nuclear power plant, terrorist attack, and dam break. Wildfires are often the result of human action but are classified in this same document as natural events. The special events class is a distinct case within the classes of man-made evacuation events, representing repeatable events (e.g., sporting events) that have attributes analogous to some evacuation events. For modeling, these special events are especially important to consider because they can be used for model calibration and validation.

- **Technological**: An event where there is a breakdown in the technological infrastructure such as a power grid failure. The New York power outage during the summer of 2003 is an example of this type of event. Small-scale technological events may include rail-based transit systems requiring emergency evacuation due to a communication or power failure.
- **Hazardous material**: An event where there is a hazardous material involved and it is impacting an area where people are present. This could include an accident on a highway involving a tanker truck or a derailed train car leaking noxious gas.
- **Nuclear power plant**: An event taking place at a nuclear power plant requiring evacuation of the surrounding community.

- **Terrorist attack**: An unknown event involving the potential harm of people and destruction of property caused by a single individual or coordinated attack by a group of individuals. This may involve a hazardous material (nuclear, biological, or chemical) or coincide with a technological event.
- **Dam break**: An event near or next to a dam (or levy) where the potential for quick and serve flooding of a nearby area is possible.
- **Special event**: An event such as a sporting game, festival, or fair. Generally these events occur either on a regular basis or there is a fair amount of time in order to plan for such an event.

2.1.3 Transportation Modeling Tools for Evacuation Planning

Over the past decade, a number of emergency evacuation models have been developed. In the 1980s, after the Three Mile Island incident, studies focused on evacuation plans of nuclear power plants, such as the Dynamic Network Evacuation (DYNEV) (KLD Associates 1981). More recently, with severe hurricanes threatening the United States, planners have placed more focus on the evacuation of coastal areas. Examples of coastal evacuation models include mass evacuation (MASSVAC) (Hobeika and Radwan 1985), Oak Ridge Evacuation Modeling System (OREMS) (ORNL 1998), and Evacuation Traffic Information System (ETIS) (PBS&J 2000). Besides the above specific modeling packages, general-purpose simulation tools, such as MITSIMLab (Yang et al., 2000), ARENA (Chien et al., 2005), VISSIM (PTV Inc, 2005), DYNASMART-P (McTrans 2007), and CUBE AVENUE (Brown et al., 2010), were also employed for evacuation planning purposes.

In a follow-up study to the evacuation tool inventory, Hardy et al. (2009) provide a general process for successful evacuation modeling analysis including “(a) identifying the decisions to be supported when conducting an evacuation modeling analysis, (b) addressing how these decisions are related or can be considered independently, and (c) developing a comprehensive transportation modeling approach that best addresses these decisions.” They assess the existing tools in terms of functionality (flexibility for use in different applications), characteristics of the desired results (detail level or the precision of the results), and scope of the analysis (macro-, meso-, and micro-modeling approaches) in terms of their capability to model a geographic area. They also mention two other important considerations: cost and maintenance of the selected tools. As also discussed in Lindell and Prater (2007), there is a trade-off between the scope of the analysis and precision of the results, as well as the data requirements needed to use the tool.

Macroscopic models can be used to model larger regions with relatively complex transportation networks; however they omit individual vehicle-related details. Microscopic models provide a great level of detail for a corridor or small network, but they are not suitable for larger networks due to computational burden and the extensive data needed for calibration. Meso-scopic models may enjoy and suffer from the pros and cons of the other two extreme approaches depending on the application. Thus, it has been difficult to apply the previous models or simulation tools to specific major concerns regarding emergency evacuation planning, including the size of the transportation networks and geographic scale used, as well as complex topology and connectivity. Moreover, developed models may employ special algorithms and software structure, which could limit the modeling of special emergency scenarios. Transportation planners and operators may be interested in not only the planning results but also the intuitive solution mechanisms that enable customized analysis.

2.2 Risk Analysis for Degradable Transportation Systems

2.2.1 Sources of Risks

Generally there is considerable uncertainty in transportation system evaluation. Capturing uncertainty in a transportation system is important for arriving at better planning decisions, both for the long-term planning and short-term operations. Pecknold (1970) investigated the short-term demand uncertainty impact on the time-staged highway investment strategies. The demand is represented by “a number of downward sloping functions, each with a certain probability of occurrence,” instead of a single point estimate. Mahmassani (1984) summarizes and categorizes the sources and types of uncertainty into five different types:

- *The unknown, consisting of new and unforeseen situations, which include major unsuspected political upheavals or changes and unanticipated technological breakthroughs.* This category is by definition outside the scope of the formal analysis of transportation options.
- *Occurrence of exogenous events or states independent of the transportation decisions made but affecting the environment in which the transportation system operates, including political events (e.g., a new administration) and economic or social circumstances.* This type of uncertainty can be represented either through discrete “states of nature” or “scenarios” (with analysis of the options’ impacts conditional upon their realization) or directly through uncertainty in the variables entering the evaluation.

- *Uncertainty, or randomness, in the values of measured or predicted impacts, which is usually the result of a modeling activity.* Examples of such variables include estimates of demands, flows on various portions of the transport network under consideration, benefit measures, costs, and many others.
- *Imprecision or vagueness in the definition of one or more criteria and the description of an option's performance along that criterion.* Examples include criteria such as "aesthetics" or "political desirability." Vagueness, or "fuzziness," is a property that concerns the very concept of a variable.
- *Uncertainty as to the preferential or normative basis of the evaluation,* which ultimately determines the outcome of the decision-making process. An example of this type is the risk attitudes of the decision maker involved in the decision process and the appropriate trade-offs among criteria.

In general, we usually refer to "Types 2 and 3 as the issue of uncertainty impact by standard statistical and probabilistic tools for transportation uncertainty evaluation" (Mahmassani, 1984). However, there are currently no universal definitions to classify the sources of disruption to the road network. Chen et al. (2002) summarizes sources of network uncertainty into four categories: (a) variations in arc capacities, (b) variations in travel demands, (c) imperfections in the route choice models, and (d) uncertainty in the parameters of the link travel time function.

This dissertation mainly focuses on the uncertainty of roadway capacity, which can be due to both exogenous and endogenous reasons. Exogenous capacity uncertainty is caused by factors that are independent of traffic flow, such as weather (Okamoto et al., 2004, Smith et al., 2004, and Agarwal et al., 2005), major natural or man-made disasters

(Ozbay and Yazici, 2007, Jha et al., 2004, and Zou and Yeh, 2005). These uncertainty-causing events usually happen randomly and can have a significant influence on link capacity.

Endogenous capacity uncertainty is mainly due to flow-dependent stochasticity, which is mainly caused by flow-related factors, such as accident rates and traffic breakdowns. On the one hand, empirical data show that the accident rate follows a certain pattern (e.g., a U-shape) for different types of infrastructure, as explained in Ceder and Livneh (1982), Hall and Pendleton (1990), Zhou and Sisiopiku (1997), and Martin (2002). On the other hand, as with accidents, the breakdown probability is also positively correlated with traffic flow and redefines the concept of capacity based on a probability level, as explained in Hall and Agyemang-Duah (1991), Persaud et al. (1998), and Lorenz and Elefteriadou (2001).

Variations in roadway capacity can be generally classified as long-term (or nonrecurrent) and short-term (or recurrent) uncertainty. Long-term capacity uncertainty mainly refers to the natural disasters (hurricane or earthquake) and man-made terrorist attacks that can cause certain links to totally collapse with a continuous impact for several months and even longer (see Waller et al., 2001, Waller and Ziliaskopoulos, 2001, as examples). Short-term capacity uncertainty mainly includes an interruption or an incident that might affect a link for less than a day and maybe few hours. The recurrent interruptions such as extreme weather and accidents may also result in severe congestion, particularly causing partial blockage of certain network links that are heavily traveled, as described in Asakura and Kashiwadani (1991), Bell et al. (1999), and Clark and Watling (2005), for example.

Both short-term and long-term capacity uncertainty may potentially degrade the performance of a road network. Nicholson et al. (2003) suggest several questions for both network users and planners that can help us understand the perspective of users and planners vis-à-vis uncertain events likely to cause capacity degradation.

Network users:

- Is it still possible to reach my destination by any route?
- Is the route that I normally take likely to be closed?
- If it is open, am I likely to encounter an unusual event (e.g., a delay)?
- What is the likely delay on my usual route?
- Should I choose a different route or mode?
- Should I postpone the trip?
- Should I choose a different destination?
- Should I cancel the trip?

Transport network planners:

- How many users will not travel to their destination?
- Which links will be congested or closed (i.e., which are weak links)?
- Which are the important links in the network?
- Which are the critical (important and weak) links?
- What are the expected economic costs of closures?

2.2.2 Measures of Risks

The above questions focus on separate aspects of transport network reliability, which can be captured using reliability measures. This section briefly discusses the main attributes of those measures.

2.2.2.1 Connectivity

Connectivity is one of basic concepts in graph theory. Consider a graph *G (V, E)* where *V* is a set of vertices and *E* is a set of edges. "A graph *G* is said to be connected if there exists a path between any pair of vertices in the graph" (Hurst, 1974). Correspondingly, for a certain origin and destination pair, if there exists a path in the graph, it can be said that this origin and destination pair is connected.

As a measure of transportation network reliability, the network is modeled by using a directed graph *G (V, E).* Each edge has a binary status—either open or closed—with certain probability. The connectivity reliability refers to the probability that connectivity exists from a certain origin to a certain destination. The value of connectivity reliability is naturally between zero and one.

The transportation network connectivity analysis was originated by Garrison (1960), who investigated the connectivity of the newly built interstate highway system compared with the railway system. This research was mainly motivated by the idea of determining the impact of connectivity changes caused by the interstate highway system on the relative location of urban centers and activities. The connectivity was measured by the maximum possible number of paths divided by the observed number of paths. Until the 1990s, the traffic congestion and the influence of uncertainty events (disaster, weather, etc.) started to draw significant attention. Wakabayashi and Iida (1992) introduced the concept of terminal reliability of road networks, which was defined as "the probability that two given nodes are connected for certain traffic service levels for given periods of time." Bell and Schmocker (2002) defined connectivity as encountered reliability or "experienced terminal reliability," which measures "the likelihood that a user experiences at least one vertex failure." In other words, it measures "the probability of not encountering a link degradation on the path with least (expected) cost." Failure refers to not only a complete failure (binary state) but also a delay and reduced capacity.

2.2.2.2 Travel Time

Connectivity measures the probability of whether travelers from a certain origin can arrive at their target destination, but it does not measure how fast they travel. In other words, the reliability of connectivity does not account for the impact caused by network degradation, which can result in short- or long-term disruptions and cause severe congestion and delay. Moreover, the connectivity is only measured by assuming the link has a binary status—namely, fully operating or completely failed. However, minor or partial link capacity reduction (i.e., incident or extreme weather) may also potentially degrade the roadway network performance especially in the presence of large evacuation demand and particularly when large populations must be expediently evacuated from dense urban areas.

Travel time reliability is defined as "the probability that a trip will arrive at its destination within a given period" (Asakura and Kashiwadani, 1991). It is a measure of the stability of travel time, which is related to the traffic flow on the link. The differences between the reliability of connectivity and travel time reliability are as follows:

On one side, instead of the assumption of the binary status of the link, travel time reliability can be used to represent different levels of capacity degradation—including minor and partial link capacity reductions, as well as complete link closure.

On the other side, travel time reliability is much more related to travelers' route choice decision, which will reflect the impact of capacity reductions on network users.

2.2.2.3 Flow Reduction

Nicholson and Du (1997) define the reliability of flow reduction as "the probability that the reduction in flow (as a result of supply-demand interaction) is not less than a threshold, for both OD pairs and the network" (Nicholson et al., 2003). It is related to the measure of travel time reliability via supply-demand interaction. When links are degraded, travel times between certain OD pairs change, affecting the route choices and thus link flows.

The reliability due to flow reduction is evaluated based on a sub-network connecting individual OD pairs. The value of the flow reduction is defined as the proportion of flow reduction under degradable conditions compared with the flows under normal conditions. Correspondingly, the reliability is defined as the probability that the network flow reduction does not exceed a given threshold value, which is preset for each sub-network. When the flow reduction exceeds the specified threshold value for that sub-network, it will be considered a failure.

2.2.2.4 Capacity

The above three reliability indices measure the different aspects of performance (connectivity, travel time, and link flow) in a degradable transportation network. However, all of the above reliability measures are post-event tools for evaluating and analyzing how badly the uncertain event affects the current transportation network. The most straightforward and proactive question about network reliability is "whether the current network capacity can accommodate the demand . . . If not, how can we improve the current network to enhance the network reliability?"

Chen et al. (1999) introduce the measure of capacity reliability as "the probability that the road network can accommodate a certain level of traffic." It is concerned with the maximum demand that a certain network can accommodate. Instead of the binary link status assumption for the reliability of connectivity, the link capacity is treated as a random variable to capture operations at multiple states, which extends the reliability measure for capturing both non-recurrent and recurrent events. Chen et al. (2002) provide a comprehensive analysis of the capacity reliability, which integrates the uncertainty analysis, network equilibrium models, and performance measures together to evaluate the performance of a degradable road network (Chen et al., 2002). However, the disadvantage of this measure is that it requires extensive numerical simulations to estimate the relationships between the network elements subject to stochastic variations and the sought performance measures (Lo and Tung, 2003).

A variation of this measure is "the maximum flow that the network can carry, subject to link capacity and link travel time reliability constraints" (Lo and Tung, 2000). The probability distribution of link capacity degradation is based on link-level incident statistics. The difference with the measure proposed by Chen et al. (1999) is the modeling approach, which relies on chance-constrained programming (Charnes and Cooper, 1963). The main advantage of this approach is that the solutions can be obtained without extensive simulations. The final outcome is a mathematical program that only needs to be solved once to obtain the desired solution (Lo and Tung, 2003).

2.2.2.5 Vulnerability

Vulnerability can be generally considered the complement of reliability. Nicholson and Du (1994) define it as "the susceptibility to incidents that result in route closures . . . it increases as the probability and/or consequence of failing to meet user expectations increases." Berdica (2002) reviews the current development on road network vulnerability and defines it as "a susceptibility to incidents that can result in considerable reductions in road network serviceability." Serviceability "describes the possibility to use that link/route/road network during a given period." The conceptual framework for analyzing vulnerability can be seen in FIGURE 2-2.

FIGURE 2-2 Vulnerability in Transportation Systems (Chen et al., 2007)

In general, this concept is concerned with the consequence of link degradation in priority, rather than the probability of link degradation. The value of vulnerability can be used to identify critical links in transportation networks, which is theoretically associated with the problem of determining the most vital arcs or edges.

2.2.2.6 Summary

The above reliability measures are specified for certain aspects of transport network reliability. As mentioned above, these reliability measures can be generally studied from the perspective of the system planner and individual user. Basically, the system planner is primarily concerned with long-term capacity interruption while the individual user pays more attention to daily short-term link capacity uncertainty. Nicholson et al. (2003) categorized all the measures by individual users and system planners. We modified the conclusion by Nicholson et al. (2003) according to the summarized categories. TABLE 2-1 and TABLE 2-2 summarize the reliability measures from the individual user's and network planner's perspectives, respectively.

TABLE 2-1 Reliability Aspects for Network Users

<table>
<tr><th></th><th>Connectivity</th><th>Travel time</th><th>Flow reduction</th><th>Capacity</th><th>Vulnerability</th></tr>
<tr><td>Is it still possible to reach my destination (which OD pairs are not connected)?</td><td>×××</td><td>×</td><td rowspan="5">N</td><td rowspan="5">N</td><td rowspan="5">N</td></tr>
<tr><td>Is the route that I normally take likely to be closed (which routes are closed)?</td><td>×××</td><td>×</td></tr>
<tr><td>If it is open, am I likely to encounter an unusual event (which user encounters such events)?</td><td>××</td><td>×</td></tr>
<tr><td>How severe are the delays on my preferred route (what delays without rerouting)?</td><td>××</td><td>×××</td></tr>
<tr><td>Is it advantageous to choose a different route or mode (delay with rerouting)</td><td>×</td><td>×××</td></tr>
<tr><td>Should I travel later (suggest postponing travel)?</td><td colspan="5">N</td></tr>
<tr><td>Should I choose a different destination or cancel the trip (provide travel advice)?</td><td colspan="5">N</td></tr>
</table>

Modified table based on Nicholson et al. (2003)

×—minimal usefulness; √√—some usefulness; √√√ ×××—good usefulness; N—no usefulness

TABLE 2-2 Reliability Aspects for System Planners

<table>
<tr><th></th><th>Connectivity</th><th>Travel time</th><th>Flow reduction</th><th>Capacity</th><th>Vulnerability</th></tr>
<tr><td>How many users will not travel to their destination?</td><td rowspan="2">N</td><td>××</td><td>×××</td><td>×</td><td>××</td></tr>
<tr><td>Which links will be congested?</td><td>×××</td><td>×</td><td>××</td><td>×</td></tr>
<tr><td>Which are the important links in the network</td><td>×××</td><td>×××</td><td>×</td><td>××</td><td>×××</td></tr>
<tr><td>Which are the critical (important and weak) links?</td><td>×××</td><td>×××</td><td>×</td><td>××</td><td>××</td></tr>
<tr><td>What are the expected economic costs of hazards?</td><td>N</td><td>×××</td><td>×</td><td>××</td><td>××</td></tr>
</table>

Modified table based on Nicholson et al. (2003)

×—minimal usefulness; √√—some usefulness; √√√ ×××—good usefulness; N—no usefulness

2.2.3 Modeling and Solution Approach

2.2.3.1 Graph Theoretical Approach

Graph Theory is widely used in quantifying the reliability of connectivity. A general performance measure for conventional network reliability analysis includes all the minimal path sets and cut sets for a certain pair of nodes, which is summarized in Bell and Iida (1997). Basically, for a series and parallel links, the network reliability (R) can be calculated as shown below:

$$R = \begin{cases} \prod_i r_i & series \quad links \\ 1 - \prod_i (1 - r_i) & parallel \quad links \end{cases} \tag{2-1}$$

Where r_i is the expected link reliability with a value between 0 and 1.

The methodology for the calculation of path or cut sets is very direct and can be easily followed. However, for large networks, it is time consuming to identify and calculate all the paths. Wakabayashi and Iida (1992) proposed an efficient method for calculating the upper and lower bounds of transportation network reliability. Kurauchi et al. (2009) applied the concept of k-edge connectivity. “The network is k-edge connected if all nodes are connected even if up to k-1 links are broken.” The results of this work can be used to create a reliability design problem and vulnerability analysis.

Besides the concept of the reliability of connectivity, a general performance measure for link vulnerability, can be the increase of the shortest path length (Malik et al. 1989, Ball et al. 1989, and Barton 2005). For example, Malik et al. (1989) and Ball et al. (1989) formulated the most vital arc problem as the determination of the subset of arcs, whose removal from the network results in the greatest increase in the shortest path length. The network connectivity performance measure in Barton (2005) is the increase in distance between the origin and sink nodes in a maximum flow graph.

2.2.3.2 Absorbing Markov Chains

As mentioned above, the calculation of the reliability of connectivity for a large network is rather expensive. Bell and Schmocker (2002) defined connectivity as encountered reliability and proposed an approach based on absorbing Markov chains.

The definition of a Markov chain is "a transition matrix with element t_{ij} t_{ij} defining the probability of a traveler moving from one given state i to another given state j." In general, the idea is to build a transition matrix for each of the travelers. For All or Nothing (AON) assignment, if no link between two nodes is available, the value of the corresponding element in the transition matrix is zero; if the transition belongs to the subpart of the shortest path, and the value of the element in the transition matrix is 1. The transition matrix in the cost of travel can be calculated as follows:

$$c_{ij} = \beta_1 d_{ij} - \beta_2 \ln(1 - f_i) \tag{2-2}$$

Where β_1 and β_2 β_2 are weights, d_{ij} is the cost ignoring unreliability, f_i f_i is the risk of failure of node i, and correspondingly $(1 - f_i)$ $(1 - f_i)$ is the reliability of node i.

The authors indicated that "the states represent the intermediate vertices of the graph, the origins, a destination and a 'bin' where trips that encounter a failure collect." The assumption of 'bin' makes the assignment more realistic: instead of predetermined link status, the traveler may encounter a network interruption with a certain probability. Instead of travel time or cost as the final output measurement, this approach only concerns the percentage of people who have ever encountered network interruption.

2.2.3.3 Game Theory Approach

Bell (2002) proposed a game theoretical approach that specifically focuses on the estimation of the upper bound of the network impact with possible link degradation. "A game is envisaged between a network user seeking a path to minimize the expected trip cost on the one hand and an 'evil entity' imposing link costs on the user so as to maximize the expected trip cost on the other." The game is a two-player, non-cooperative, zero-sum game.

Bell (2002) formulated a max-min model that is very similar to a bi-level model. At the lower level, vehicles select routes to achieve minimum cost, the goal of user equilibrium or system optimality; at the upper level, links that maximize network performance deterioration as a result of their degradation are identified. The probability of link deterioration is predetermined and reflects the vulnerability of that link. The total increased traveler's cost is considered the output measure. The expected link cost is used for traveler route choice process.

The general process for the game is, "The user guesses what link costs will be imposed and the evil entity guesses which path will be chosen." In other words, the strategy of the evil entity and the user route choice are correlated with each other. In general, it is an action-reaction process. Link failure probabilities affect users' route choice, which causes the network evil entity to change the failure probabilities. This iterative process continues until the route choice probabilities and link failure probabilities convergence to a certain stable value. This convergence point is called a mixed strategy Nash equilibrium, which is defined as "an equilibrium situation in the sense that neither the network evil entity nor the network user can further improve their route choice probabilities or link failure probabilities which can be used to calculate the above mentioned reliability measures."

2.2.3.4 Monte Carlo Simulation

The Monte Carlo simulation method uses random sampling to study properties of systems with components that behave in a random fashion. More precisely, the idea is "to simulate on the computer the behavior of these systems by randomly generating the variables describing the behavior of their components" (Lemieux 2009). This method is widely used in various areas, such as operations research, management science, engineering, finance, and especially complex system analysis.

The application of Monte Carlo simulation in transportation network analysis can be found in Dalziell and Nicholson (2001) and Chen et al. (1999). Dalziell and Nicholson (2001) use Monte Carlo simulation to generate the probability distribution of link closure, which is caused by hazards. A similar approach can also be seen in Chen et al. (1999), which models realization of random link capacity using Monte Carlo simulation. "Given the complexity of the interactions between variables describing or affecting transport system performance, and the complexity of the hazard mechanisms affecting link capacity or availability, it is likely that Monte Carlo simulation will receive increasing use in future network reliability studies" (Nicholson et al. 2003).

The main concern of using Monte Carlo simulation is the large number of samples required for a high level of accuracy, which may potentially be computationally too expensive for large networks. However, with the rapid development of high-speed computers and large-capacity storage, this drawback has been reduced in recent years (Chen et al., 2002).

2.2.3.5 Chance-Constrained Programming

Lo and Tung (2000) introduced the chance-constrained programming approach to calculate the maximum flow that the network can carry, subject to link capacity and link travel time reliability constraints. The objective of this mathematical formulation is similar to the model described in Chen et al. (1999). However, instead of probabilistic reliability requirements as introduced by using Monte Carlo simulation in Chen et al. (1999), the chance-constrained programming approach is formulated as a deterministic problem. The link capacity reliability constraint is defined as the probability that traffic flow on a link exceeds its capacity, referred to as α_a. The mathematical formulation of this constraint is shown below:

$$P(x_a \geq C_a) = P(C_a \leq x_a) \leq \alpha_a \qquad (2\text{-}3)$$

Where the subscript a refers to a particular link and the variables x_a x_a and C_a C_a are the traffic flow and capacity of link a, respectively. The capacity of a link is subject to stochastic degradations, which depend on incident statistics collected at the link level to estimate the probability distributions of link capacity degradations.

One distinct advantage of the chance-constrained approach is that solutions can be obtained without extensive simulations. The final result is a mathematical program that needs to be solved only once to obtain the optimal solution. The chance-constrained programming is widely applied in various areas (see Yazici and Ozbay 2008, 2010, Ukkusuri et al. 2009, and Waller et al. 2001).

2.2.4 Risk Analysis in the Decision-Making Process

2.2.4.1 Risk Analysis

Risk analysis in the decision-making process can be traced back to Neumann and Morgenstern (1944), who used the concept of expected utility for investigating the impact of risks on decision choices. The risks of uncertain outcomes with corresponding probabilities are considered separate choices, and the decision maker prefers the choice that could maximize the total expected utility. Mathematically, in order to compare two choices with random outcomes X and Y, the decision maker prefers the choice with random outcome Y to the choice with X.

$$E[u(X)] < E[u(Y)] \tag{2-4}$$

$u()$ is the utility function, which is assumed to be convex and non-decreasing. A simple example with the above formulation is a portfolio selection problem: when given a choice of a sure bet of 50 dollars compared with a choice 60:40 chance of winning 100 or 0 dollars, the decision maker will prefer to the latter one according to the expected utility theory. However, it's usually argued that expected utility theory emphasizes risk-neutral decision making but does not consider risk averseness, which could be considered as the trade-off variance as the potential impact factor on decision behavior. For the simple example shown above, a certain number of people would prefer the sure bet, even though the latter choice is better on average. Moreover, for practical implementation, it's not trivial work to model the utility function of a decision maker.

Another popular way to model risk in the decision-making process is the mean-risk model. The main idea of the mean-risk model is to capture the uncertain outcome by two characteristics—namely, the mean and dispersion measure. The value of the mean describes the expected outcome, and the value of the dispersion measure demonstrates the uncertainty of the outcome. The mathematical formulation is given below:

$$\rho[\cdot] = E[\cdot] + \lambda D[\cdot] \tag{2-5}$$

Where ρ [·] is mathematically defined as a mapping that assigns a real number to a measurable function. For example, a common measure in transportation planning is the total system users' time. E[·] is the expected value of this measurable function. λ is a nonnegative weight parameter, and D[·] refers to some dispersion statistics, which can also be considered a risk measure. An example of the dispersion measure is the variance, which was first applied in portfolio selection in Markowitz (1952). The value return of the portfolio selection is modeled as a trade-off between the expected payoff and the variability of the payoff. The efficient solutions claim that for a given value of the mean, they minimize the risk, and for a given value of risk, they maximize the mean. Compared with expected utility theory, mean-risk analysis is better for the trade-off analysis between the expected outcome and potential risks. Moreover, with the proper risk measure setting, the model can be treated as a convex optimization problem and solved by a number of well-known methods.

2.2.4.2 Decision Making Measures

Let *Z* denote a measurable function (e.g., total system users' time in traffic assignment). Several common risk measures that use *Z* are given below:

TABLE 2-3 Several Common Risk Measures

Risk measures	Mathematical formulation
Mean variance	$E[Z]+\lambda E[Z-E(Z)]^2$
Mean-mean absolute deviation (Mean-MAD):	$E[Z]+\lambda E\mid Z-E(Z)\mid$
Value at risk (VaR)	$VaR_\alpha[Z]:=\min\{\gamma:\Pr\{Z\le y\}\ge\alpha\},\alpha\in[0,1]$
Conditional value at risk (CVaR)	$CVaR_\alpha[Z]:=E(Z\mid Z\ge VaR_\alpha[Z]),\alpha\in[0,1]$

The classical Markowitz model (Markowitz, 1952) uses mean variance as the risk measure. The advantage of this measure is its computational convenience in cases where *Z* is linear. However, from the perspective of risk measurement, mean variance has many drawbacks. First, mean and variance are measured in different units. Second, variance is a symmetric statistic, and it penalizes gains and losses equally. Third, mean variance does not preserve the convexity of the cost function. Fourth, mean variance is not consistent with second-order stochastic dominance, which formalizes risk-averse performance. Fifth, the variance is inappropriate when describing the risk of lower-probability events.

Mean-MAD is an attractive and promising risk measure used in the area of financial engineering. This is partly due to its nice mathematical properties. For example, it is coherent and consistent with second-order stochastic dominance when $0\le\lambda\le0.5$ $\lambda\in[0,0.5]$. A more important reason is MAD's similarity with variance: the former is the mean "absolute" deviation from the mean, while the latter is the mean "squared" deviation from the mean. Given the shortcomings of mean variance mentioned earlier, a number of researchers have attempted to replace variance with MAD.

VaR is a relatively simple risk measurement notion with only a single number measuring risk. The value of VaR has a clear interpretation: how much you may lose with a certain confidence level. Another important property of VaR is stability of the estimation procedures. Because VaR disregards the tail, it is not affected by very high tail losses, which are usually difficult to measure. However, the disadvantage of VaR is that it does not account for properties of the distribution beyond the confidence level. Thus, risk control using VaR may lead to undesirable results for skewed distributions. Moreover, VaR is a nonconvex and discontinuous function for discrete distributions. For example, in a financial setting, VaR is a nonconvex and discontinuous function with respect to portfolio positions when returns have discrete probability distributions. This makes VaR optimization a challenging computational problem.

CVaR has a clear engineering interpretation. It measures outcomes that have the highest negative impact. Moreover, defining $CVaR_{\alpha}[Z]$ for all confidence levels completely specifies the distribution of *Z*. In this sense, it is superior to standard deviation. The most important advantage for CVaR is that it has several attractive mathematical properties (Shapiro et al., 2009). CVaR is a coherent risk measure. $CVaR_{\alpha}[Z]$ is continuous with respect to α. CVaR of a convex combination of random variables $CVaR_{\alpha}(\omega_1 X_1 + \cdots + \omega_n X_n)$ is a convex function with respect to $(\omega_1, ..., \omega_n)$. The disadvantage for CVaR is that it is more sensitive than VaR to estimation errors. If there is no good model for the tail of the distribution, the CVaR value may be quite misleading, and accuracy of CVaR estimation is heavily affected by accuracy of tail modeling.

2.2.4.3 *Applications in Engineering and Transportation Problems*

The mean-risk model is originally proposed in the finance area for portfolio selection. Markowitz (1952) first combined the potential risk and expected return as the objective function. Such an approach has many advantages. It allows one to formulate the problem as a parametric optimization problem, and it facilitates the trade-off analysis between the mean and the risk. Markowitz (1952) used variance of the investment return to measure the potential risk because of its analytical tractability. The subsequent studies also investigated several other risk measures, such as mean absolute deviation, value at risk, and conditional value at risk. For a recent summary of risk measures, we refer the reader to Shapiro et al. (2009). The mean-risk model and above-risk measures are also widely applied in other areas, such as industrial, biological, and civil engineering (see Linares 2002, Nagengast et al. 2011, and Gupta and Maranas 2003).

Recently several studies have used the mean-risk model to assess the performance of transportation facilities. Liu et al. (2009) focus on the network retrofit problem, which attempts to optimize the limited resources to improve the resilience and robustness of the entire transportation system. For capturing the extremely high uncertainty in the decision environment, the model is formulated by using the mean-risk objective of the system loss. An efficient algorithm is proposed by extending the well-known L-shaped method using generalized benders decomposition. Ban et al. (2009) pointed out that the existing second-best toll pricing (SBTP) models are risk prone if the traffic assignment has multiple solutions. A risk-averse SBTP is proposed to optimize the worst-case scenario. The mathematical model is formulated as min-max problem. Guo and Verma (2010) investigate the risk and route selection domains of hazardous materials. They argue that the frequently used expected consequence approach is not appropriate for rare events because it ignores the risk-averse behavior. For the expected consequence approach, such low-probability, high-consequence events are treated as the same as high-probability, low-consequence events. Usually the low-probability, high-consequence events are a function of hazmat volume. Guo and Verma (2010) attempt to investigate the truck capacities on transport risk. Seyedshohadaie et al. (2010) propose a method for determining optimal risk-based maintenance and rehabilitation policies for transportation infrastructure. The proposed policies guarantee a certain performance level across the network under a predefined level of risk. Noyan (2011) proposes a risk-averse stochastic programming model, where the conditional value at risk is used as a risk measure. Two decomposition algorithms based on the generic Benders decomposition approach is also proposed to solve such problems. The proposed model and algorithms are applied to disaster management as a case study.

2.3 Summary

This section provides a review of transportation planning for evacuations and risk analysis for degradable transportation systems.

For decades we have focused on transportation planning with the traditional criteria including accessibility, mobility, environment, safety, and so forth. However, traditional transportation planning needs to be revised by considering the requirement of transportation security, which focuses on analyzing the vulnerability of transportation systems to natural or man-made disasters.

Transportation systems play an active role in supporting and assisting evacuation operations. The review of current practices by Wolshon (2008) shows that transportation personnel is involved in several of the above components via managing and maintaining transportation systems, including traffic planning, monitoring, control, and management.

In the emergency response context, an efficient evacuation route–planning model has the utmost importance due to increased focus on the risks of natural and man-made disasters. Over the past decade, a number of emergency evacuation models have been developed. Historically, evacuation modeling tools have targeted specific events rather than general-purpose events. For example, the tool DYNEV was created in response to the Three Mile Island nuclear power plant accident. Similarly, the tool HURREVAC was a reaction to the presence of hurricanes along the coasts.

For risk analysis in degradable transportation systems, according to Mahmassani (1984), risks are generally grouped into five categories. We refer to Types 2 and 3 as the issue of uncertainty impact by standard statistical and probabilistic tools for transportation uncertainty evaluation. The uncertainty can also be generally categorized as exogenously/endogenously determined capacity uncertainty, and long-term/short-term capacity uncertainty.

Measure of uncertainty can be generally divided into five groups: connectivity, travel time, flow decrement, capacity, and vulnerability. The above reliability measures can also be generally separated for system planners. Basically, the system planner is concerned with long-term capacity interruption in priority while the individual user pays more attention to daily short-term link capacity uncertainty.

For uncertainty modeling, we review five different kinds of modeling approaches: graph theory, absorbing Markov chains, game theory, Monte Carlo simulation, and chance-constrained programming. The above approaches are correlated with uncertainty measures: graph theory, absorbing Markov chains, and game theory are generally used for connectivity analysis, and Monte Carlo simulation and chance-constrained programming are widely used for other uncertainty measurement analysis.

3 EVACUATION TRAFFIC MODELING: A FRAMEWORK VIA REGIONAL TRANSPORTATION PLANNING TOOLS

Evacuation modeling and analysis is primarily concerned with identifying the types of traffic movements associated with disaster evacuation and evacuation routes, as well as estimation of evacuation and clearance times. Thus, an efficient evacuation planning model is of the utmost importance in determining evacuation times, identifying critical locations in the transportation network, and assessing traffic operations strategies and evacuation policies.

This chapter presents an evacuation modeling framework by utilizing widely available regional transportation planning tools. In order to address the static nature of the planning tool, a pseudo-dynamic procedure that entails running consecutive traffic assignments with short time intervals is proposed. The traffic is dynamically updated for each time interval under equilibrium condition by considering residual demand from the previous interval. The proposed procedure is tested with a case study using a developed regional travel demand model.

3.1 Introduction

Many public planning agencies have already developed travel demand models used for planning purposes. Such models have a detailed representation of the transportation network and have been well calibrated for the study area. Using these existing tools for evacuation modeling saves time and cost while providing the desired planning outcomes for emergency planners. However, evacuation is a unique event that possesses different aspects compared to the daily/nonemergency conditions that these tools are developed for.

Hence, there is a need to make adjustments to these tools in an evacuation application. This study aims to provide a framework for an existing regional demand model to study the evacuation of the region under a variety of potential threats. Regional demand models are available in many regions and have been well calibrated for the area.

In order to capture the potential congestion during evacuation process, a pseudo-dynamic procedure is developed and employed. The logic of the pseudo-dynamic procedure is based on running consecutive traffic assignments with short time intervals and updating the traffic based on how much of the existing traffic will stay as residual traffic during the following assignment period. If the scenario specifications allow for the use of an existing general-use transportation planning model, the proposed methodology can be used for customizing the selected tool to make inferences for the scenario-related case studies. Finally, the methodology's application and analysis of results are presented using the North Jersey Regional Transportation Model–Enhanced (NJRTM-E), a travel demand model developed by the North Jersey Transportation Planning Authority (NJTPA).

3.2 Modeling Framework

The proposed procedure for customizing an existing planning tool for evacuation analysis is briefly explained in a generic manner that fits multiple scenarios. In the following section, a detailed description is provided within the context of a pseudo-dynamic traffic assignment procedure. The proposed process for determining evacuation modeling methodology consists of the following steps:

Determination of the evacuation region: The region to be evacuated (evacuation zones) determines the population at risk, the corresponding level of evacuation demand,

and the area where the evacuation-related security measures will be implemented. The evacuation zone borders are based on the threat/disaster that triggers the evacuation and are dictated by the scenario specifications. For instance, the evacuation zone for a toxic gas release may be based on the region that is covered by the toxic plume under prevailing winds, and different definitions of the evacuation zone can be assigned for varying levels of intensity or wind patterns.

Preparation of evacuation trip tables: Evacuation trips are different than daily trips in terms of the trip purpose, destinations, and mode choices. Regular daily trips are based on economic/household activities between attraction points anywhere in the network, whereas evacuation trips are mostly mandatory trips directed out of the disaster impact area. The mode choice decision mechanism is also different for emergency conditions. For areas outside of the evacuation zone, the daily activities can be assumed to prevail; hence the existing trip tables do not need any adjustment. However, for the evacuation zone, the trip tables should be adjusted to reflect the number of people who will evacuate (trip generation), their evacuation destinations (trip distribution), and the mode choice. Meanwhile, there will be background traffic inside the evacuation zone due to short trips such as shopping trips or pre-evacuation trip chaining or those who ignore evacuation orders. Evacuation-specific surveys are needed to determine the evacuees' decision process and prepare trip tables for evacuation conditions.

Transportation network adjustments: The disaster/event that causes the evacuation may have impacts on the transportation network that the planner would not incorporate for regular planning purposes, such as link capacity disruptions due to flooding or infrastructure loss due to a targeted attack. The evacuation scenario may also incorporate operational aspects such as contra-flow operations during a hurricane evacuation or blocking certain roadways/routes to disallow traffic from a particular area. In such cases, the existing transportation network needs to be modified via new capacity assignments.

Analysis of model output: Based on the literature, there are two critical outputs of evacuation studies for planners and emergency management officials: evacuation times (clearance and average travel times) and network bottlenecks. The clearance time is based on an assumed point of safety rather than the final evacuation destinations. The clearance and average travel times can be calculated by tracing the travel times between the nodes inside the evacuation zone and nodes on the evacuation zone boundary. In the case of traditional static assignment, the mobilization and staging times cannot be accounted for in the clearance time since all trips begin at the same time. However, incremental assignment can be used to provide these estimates.

To locate critical links in the network, the loaded network can be analyzed in terms of volume/capacity (V/C) ratio, which indicates the level of congestion in each link. The major bottlenecks in the network can be determined based on the highest V/C values. Local bottlenecks (e.g., local roads, few consecutive links connecting to major arterials) and congested corridors (e.g., a large segment of a roadway consisting of many consecutive congested links) can be identified based on the V/C ratios. The local bottleneck locations are valuable inputs to emergency planners preparing evacuation congestion mitigation policies to allow evacuees to reach major roadways by avoiding local bottlenecks. On the other hand, identified congested corridors can be targeted for implementation of management strategies to increase evacuation efficiency, such as contra-flow.

3.3 Pseudo-dynamic Traffic Assignment Procedure

Travel demand models mainly employ static traffic assignment, which uses calibrated trip tables for different time-of-day periods. Typically, two types of traffic assignment can be performed: user equilibrium (UE), which assumes that users reach equilibrium when they cannot improve their travel time by switching to alternate routes, and system optimum (SO), which estimates link flows based on some system-wide objective (e.g., minimization of travel time). This static network analysis is generally based on mean values, such as travel time, travel distance, or level of congestion. From Sheffi (1981), the static assignment formulation is as follows:

$$
\begin{aligned}
& SO:\ \mathrm{Min} \sum_a x_a t_a(x_a) \ \text{ or UE}:\ \mathrm{Min} \int_0^{x_a} t_a(\omega)\,d\omega \\
& s.t. \\
& \sum_k h_k^{rs} = q_{rs} \qquad \forall \mathrm{r,s} \\
& h_k^{rs} \geq 0 \qquad \forall \mathrm{r,s} \\
& \mathrm{x_a} = \sum_{\mathrm{r}} \sum_{\mathrm{s}} \sum_{\mathrm{a}} \mathrm{h_k^{rs}} \delta_{\mathrm{a,k}}^{\mathrm{rs}} \ \forall a
\end{aligned} \tag{3-1}
$$

Where q_{rs} is the OD flow from origin r to the destination s, h_k^{rs} is the flow on the path k from r to s, $\delta_{a,k}^{rs}$ is a binary value indicating that link a exists on path k between r and s, x_a is the flow on link a, and t_a is the travel time of link a.

Due to the nature of static traffic assignment, trips are assigned to the network at once, and the link volumes and corresponding travel times are calculated based on equilibrium assignment. For evacuation scenarios such as a bomb threat or other man-made incidents, the mobilization time is assumed to be short; evacuees are assumed to respond to the threat immediately and leave the evacuation zone as quickly as possible. Hence, static assignment may adequately represent such no-notice evacuations since the evacuees are loaded onto the network at once. However, for advance-notice events (e.g., hurricanes), the evacuees do not necessarily evacuate all at once or in the same time period. Moreover, the departure timings of evacuees may show high variations along a single time period, which may require shorter analysis time intervals to incorporate the demand variance.

We propose a pseudo-dynamic assignment with shorter time periods where trips not achieving completion within a given time interval are rolled into the following period and subsequently so until completion. In a pseudo-dynamic assignment, time steps can be user defined and shorter, but manual adjustments to the capacities of subsequent time periods must be made to represent the loss of available capacity due to the demand of trips from the previous time step that have yet to be completed. Furthermore, the time to completion for certain trips may be excessively long due to the restrained capacity. The pseudo-dynamic assignment formulation at time step τ is as follows:

$$
\begin{aligned}
&SO:\ \mathrm{Min}\sum_a x_a^\tau t_a^\tau(x_a^\tau + r_a^{\tau-1}) \text{ or UE: } \mathrm{Min}\int_0^{x_a} t_a^\tau(\omega^\tau + r_a^{\tau-1})d\omega^\tau \\
&s.t. \\
&\sum_k h_k^{rs,\tau} = q_{rs}^\tau \qquad \forall \mathrm{r,s},\tau \\
&h_k^{rs,\tau} \ge 0 \qquad \forall \mathrm{r,s},\tau \\
&r_a^{\tau-1} = \begin{cases} x_a^{\tau-1} - c_a^{\tau-1}, if\ x_a^{\tau-1} \ge c_a^{\tau-1} \\ 0, else \end{cases} \\
&\mathrm{x}_a^\tau = \sum_{\mathrm{r}}\sum_{\mathrm{s}}\sum_{\mathrm{a}} \mathrm{h}_{\mathrm{k}}^{\mathrm{rs},\tau}\delta_{\mathrm{a,k}}^{\mathrm{rs},\tau}\ \forall a \\
&x_a^0 = c_a^0 = 0, \tau = 1,2\ldots N
\end{aligned}
\tag{3-2}
$$

Where $r_a^{\tau-1}$ is the residual evacuation demand that not completed at time step $\tau-1$, $c_a^{\tau-1}$ is the link capacity at time step $\tau-1$, q_{rs}^τ is the OD flow from origin r to the destination s at time step τ, $h_k^{rs,\tau}$ is the flow on the path k from r to s at time step τ,

$\delta_{a,k}^{rs,\tau}$ is a binary value indicating that link a exists on path k between r and s at time step τ, x_a^τ is the flow on link a at time step τ, $t_a^\tau()$ is the travel time of link a at time step τ, and N is the maximum time step. The overall flowchart of modeling procedure with pseudo-dynamic traffic assignment is shown in FIGURE 3-1.

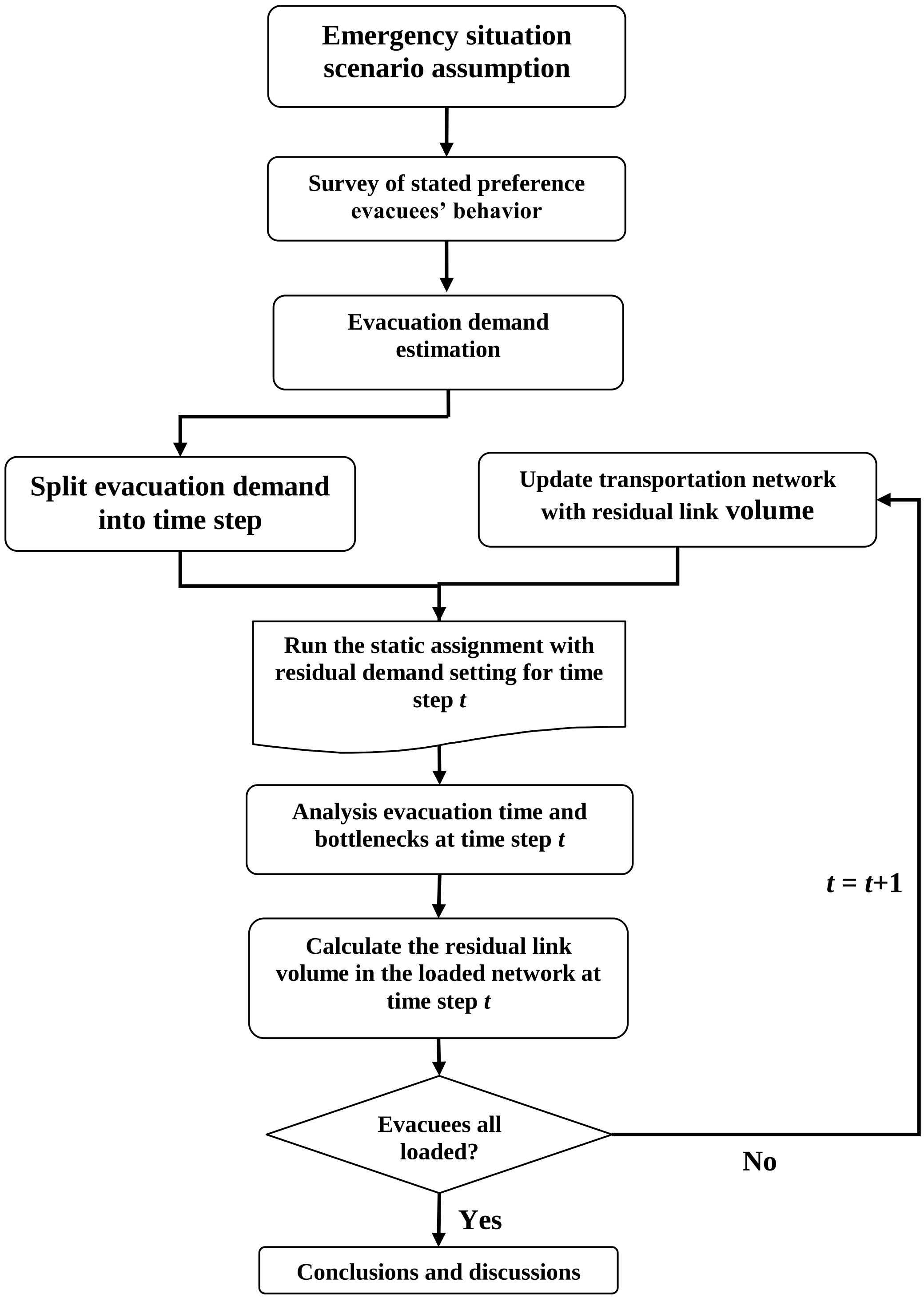


FIGURE 3-1 Flowchart of the Proposed Pseudo-Dynamic Assignment Methodology

3.4 Case Study: Hurricane Evacuation of Northern New Jersey

3.4.1 Evacuation Modeling Platform

For the evacuation modeling of a region the size of northern New Jersey, microscopic simulation is impractical due to time, budget, and computational constraints. Likewise, the model development and calibration for using a dynamic traffic assignment (DTA) model for this type of very large and complicated network is equally difficult if not impossible. On the other hand, the North Jersey Regional Transportation Model–Enhanced (NJRTM-E) is a well-calibrated model developed by North Jersey Transportation Planning Authority (NJTPA) in CUBE and has been used in the region for various planning purposes. NJRTM-E covers all of northern New Jersey, as well as adjacent portions of New York and Pennsylvania. There are four separate networks for the four different times of day in the model: AM peak (6:00 a.m.–9:00 a.m.), midday (9:00 a.m.–3:00 p.m.), PM peak (3:00p.m.–6:00 p.m.), and night (6:00 p.m.–6:00 a.m.) (NJTPA 2008). The four-step planning model utilizes an equilibrium traffic assignment with each of the four time-of-day periods' traffic assignments conducted individually. NJRTM-E trip tables include eight different trip purposes covering a range from home-based work trips to shopping, non-work, university, and other trips. This wide trip purpose coverage allows the planner to incorporate the impact of economic activities in non-evacuating regions on the evacuation performance of affected regions. The zone structure of the model is compatible with existing census and other demographic data.

3.4.2 Resident Evacuation Surveys

Telephone surveys are conducted (in English or Spanish) for random samples taken from seven counties in New Jersey. Scenarios describe disaster scenarios and the possible conditions that might be experienced at immediately after a disaster. Overall, the survey makes it possible to examine the evacuation decision changes across different threats and within varying proximities to the disaster location, along with the overall evacuation destinations and mode choice. More details about the survey can be found in Carnegie and Deka (2010).

The resident evacuation survey data include the necessary information regarding the evacuee decision process. For example, in a hurricane evacuation, a categorical analysis and regression tree (CART) model is developed for evacuation behavior based on the survey data. The population statistics that exist in the NJRTM-E model are enhanced with census information to find the number of evacuees at the census tract level in the NJRTM-E network. The traffic assignment is performed with the car-only evacuation demand and transit usage percentage obtained from the resident evacuation survey.

3.4.3 Evacuation Demand Loading

Once the total evacuation demand is calculated, the next step is determining when and how to load them to the network. For hurricanes, a behavioral response curve (S-curve), is predominantly used in hurricane evacuation studies (FEMA & Army Corps of Engineers 1995). In this scenario, evacuees are assumed to leave their houses gradually following an evacuation order issued early in the morning, according to the loading curve. The mathematical formulation of the S-curve is as follows:

$$P(t) = 1 / \{1 + \exp[-\alpha(t - H)]\} \tag{3-3}$$

Where

P(*t*) is the cumulative percentage of total trips generated at time *t*.

α is a parameter representing the response of the public to the disaster that alters the slope of the cumulative traffic-loading curve.

H is half loading time (the time when half the vehicles in the system have been loaded onto the highway network). To be more specific, *H* defines the midpoint of the loading curve and can be varied by the user according to disaster characteristics.

For the hurricane evacuation demand loading assumptions, the evacuation period is assumed to be throughout the day and the evacuees do not necessarily evacuate in the same time period. The evacuees are loaded onto the network following the behavioral response (sigmoid, or S-curve) shown in FIGURE 3-2 with a starting time of 6:00 a.m. The resident evacuation survey exhibits a network-wide scattered evacuation destination preference without any pattern. A pseudo-dynamic traffic assignment is employed as a method to introduce time dependency into the scheduling of evacuation trips.

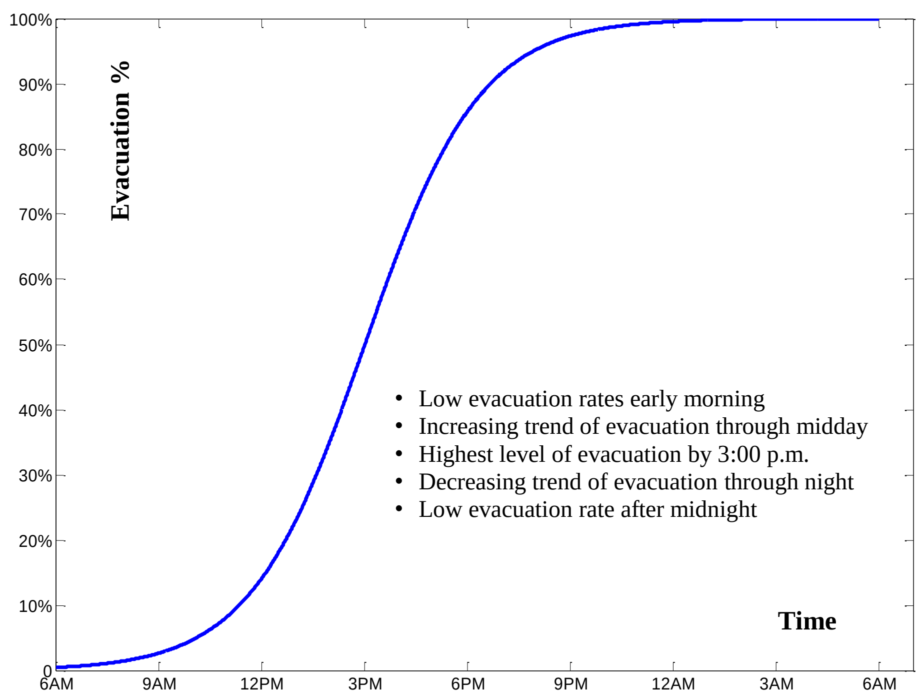


FIGURE 3-2 Behavioral Response Curve (S-Curve) for Hurricane Scenario

3.4.4 Evacuation Time Estimation

The logic of pseudo-dynamic traffic assignment is based on running consecutive traffic assignments with short time intervals and updating the traffic based on how much of the existing traffic will stay as the residual traffic before the following assignment period. For this purpose, the NJRTM-E model is run with smaller time intervals than the time-of-day periods. Each time-of-day period is divided into one-hour time intervals, and the excess volumes over the link capacities are set as the residual volumes that will stay in the network. A similar approach is also used in MASSVAC *(*Hobeika and Radwan 1985) with smaller time intervals—however, for limited network structures and evacuation demand. In order to compare the pseudo-dynamic assignment with the default static assignment for the transportation planning tool, the NJRTM-E traffic assignment model is also run with the percentage of evacuation demand for each time-of-day period. FIGURE 3-3 shows the difference in the loading patterns for time of day and hourly pseudo-dynamic assignment and the accompanying difference in evacuation clearance times. Compared with the static model, the result of pseudo-dynamic assignment is more conservative.

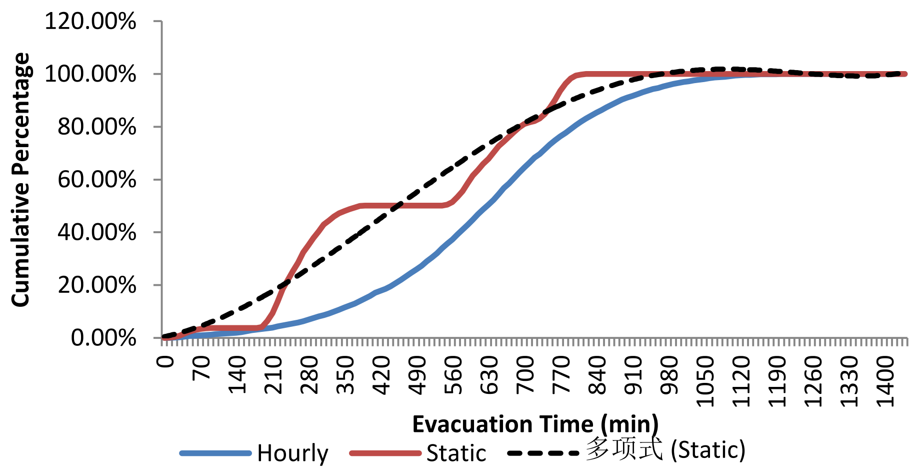


FIGURE 3-3 Clearance Times for Static and Pseudo-dynamic Assignments

3.4.5 Critical Bottleneck Links

In addition to evacuation and clearance time estimates, the major finding from the scenario analysis is identification of bottlenecks and critical links in the network. Figure 3-4 shows the congestion in the network during the chemical spill evacuation based on volume-to-capacity (V/C) ratio. In this network, links with a high V/C ratio are highlighted. The evacuation process started at 6:00 a.m. to 9:00 a.m., the congestions happened along the south part of Garden State Parkway, which is a major north–south corridor along the shore. The congestion spread to the whole Garden State Parkway and other major evacuation routes at 12:00 p.m., and the worst network performance could be observed during 12:00 p.m. to 9:00 p.m. During the night period (9:00 p.m. to 3:00 a.m.), the network congestion tailed away.

By collecting these links, emergency management officials can have an idea of which roadways are expected to face the highest demand hour by hour and potentially employ other management strategies. Local bottleneck locations are candidate locations for police presence or traffic assistance to allow local populations evacuation access to major highways and regional routes. Congested corridors can be targeted for implementation of management strategies to increase evacuation efficiency, such as contra-flow operations.

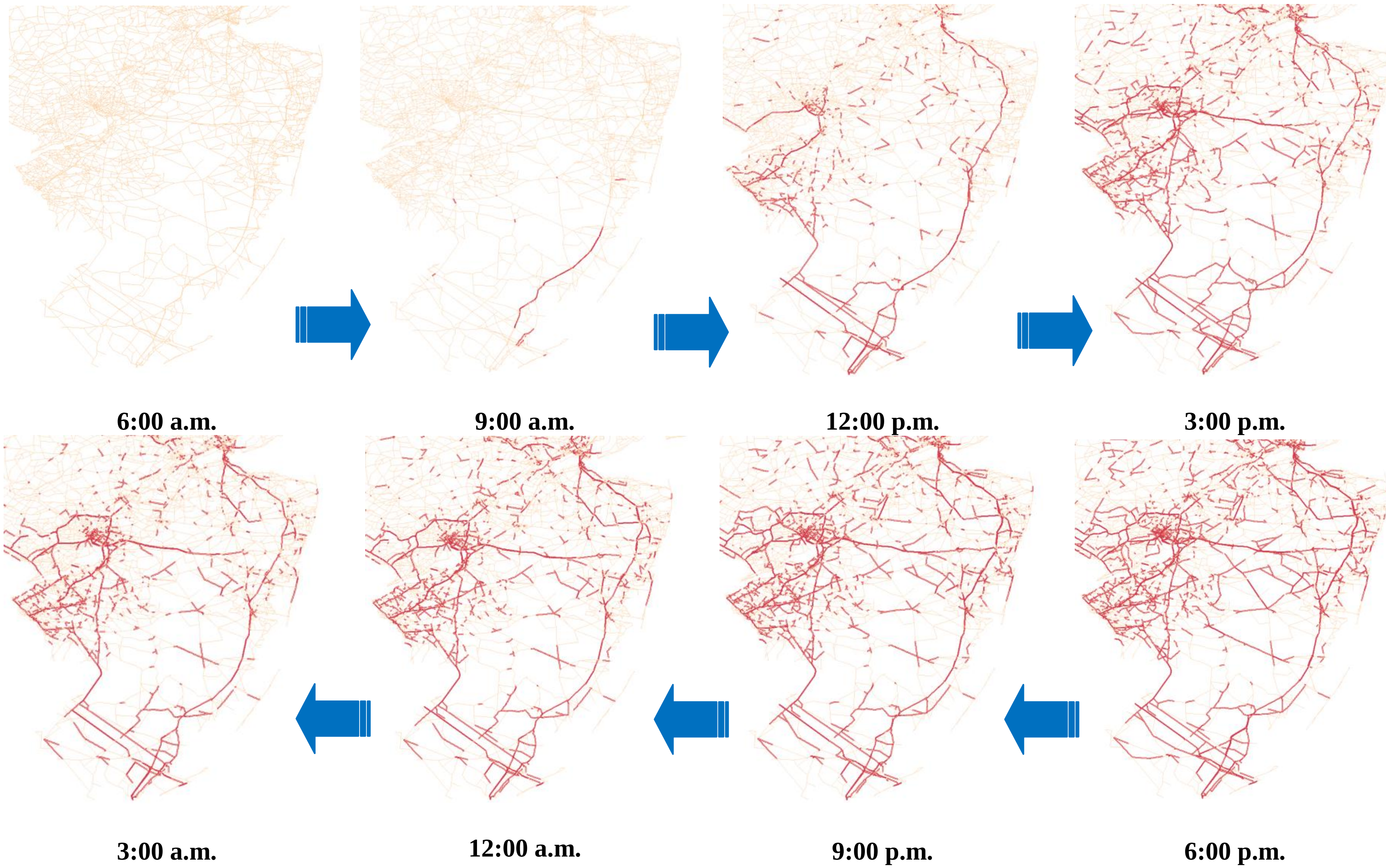


Figure 3-4 Congestion in the Transportation Network Identified by V/C Ratios

3.5 Summary

This chapter illustrates a practical pseudo-dynamic evacuation modeling procedure for conducting a regional evacuation planning study using a regional transportation planning tool. Based on the northern New Jersey network, the results of the proposed procedure shows that a regional planning model is a suitable tool for evacuation modeling and analysis, even for extended evacuation scenarios such as during a hurricane alert. In general, a pseudo-dynamic evacuation modeling procedure is a more conservative estimator than typical time-of-day static assignment periods and can be used when considerations are given to requirements such as mobilization time or staged evacuation. Given the difficulty of building and calibrating a regional transportation model solely for emergency evacuation purposes, the proposed framework allows the evacuation planner to use an existing familiar and trusted transportation model with some modifications while conducting an evacuation planning study, saving time and budget.

4 DEGRADABLE TRANSPORTATION SYSTEMS: A STATISTICAL SAMPLING APPROACH TO INCORPORATING SYSTEM VARIABILITY INTO EVACUATION MODELING FRAMEWORK

The evacuation modeling framework in the previous chapter makes it feasible to evaluate the efficiency of evacuation plans. However, evacuation planning presents numerous additional challenges including the need for capturing the impacts of uncertain events, such as potential loss of vital transportation links due to traffic accidents and adverse weather conditions. Those degradations in transportation networks may cause significant congestions and delay the evacuation process.

A common approach for evaluating system variability is using a sampling technique that randomly selects subsets of the uncertainty set to obtain an approximate solution. This chapter proposes an analytical methodology and efficient solution procedure to evaluate evacuation planning considering the system variability, such as the impacts of uncertain events (e.g., incident, extreme weather). Sample average approximation (SAA) is employed to generate plausible realizations of network degradation conditions and solve the stochastic programming. Moreover, Latin Hypercube Sampling (LHS) in order to obtain an efficient sample size for the SAA methodology.

4.1 Introduction

It is well known in the literature that capturing uncertainty in transportation system evaluation is important for arriving at better planning decisions (2), especially for evacuation planning which is closely related to the evacuees' survival rate. However, primarily due to the difficulties of data collection and computational complexity, in the current state of practice, the efficiency evaluation of evacuation planning considering uncertainty event impact and corresponding reliability analysis on evacuation time has received insufficient attention. The evaluation of possible traffic management scenarios conducted for so-called “expected” conditions assumes that the evacuation routes are going to operate under almost ideal conditions such as clear weather, average demand, and no potential accidents. Unfortunately, the use of “expected” ideal conditions as inputs does not lead to very realistic “expected” results. For example, during Hurricane Rita evacuation, severe traffic congestion was experienced due to incidents (Bowman, 2006).

Incorporating transportation system variability into the modeling process has drawn significant interest in recent years because of the emerging need to generate more realistic transportation plans. The driving force behind this new interest is the need for more robust transportation plans, especially for critical scenarios such as those involving emergency management operations and evacuations. In order to model transportation system variability, such as incident/accident and adverse weather conditions, roadway capacity is usually treated as a random variable under certain distribution instead of as a determined value in transportation planning tools (Chen et al., 1999, 2002; Lo and Tung, 2000). Such a problem is generally called the traffic equilibrium problem under capacity uncertainty (TEPCU).

Latin hypercube sampling (LHS), first introduced by McKay et al. (1979), is a stratified sampling method that can significantly reduce the variance in the MC estimate of the integrand. When sampling d input variables, the range of each input variable is divided into n equally probable bin fractions. Then, for each input variable, one observation is randomly selected, and all of these selections are combined as the first sample. The above procedure from the remaining observation of each input variable is repeated until a sample size of *n* is obtained. An example of LHS with two input variables and five bin fractions is shown in FIGURE 4-1. Note that this method samples only once for each bin fraction of input variable and that no additional required samples are needed for more variables with predetermined numbers of bin fractions. Compared to MC, LHS requires fewer samples to achieve similar accuracy. Moreover, it is more "efficient for estimating statistical moments (mean, variance, etc.) and produces more stable results than MC" (Helton and Davis, 2003).

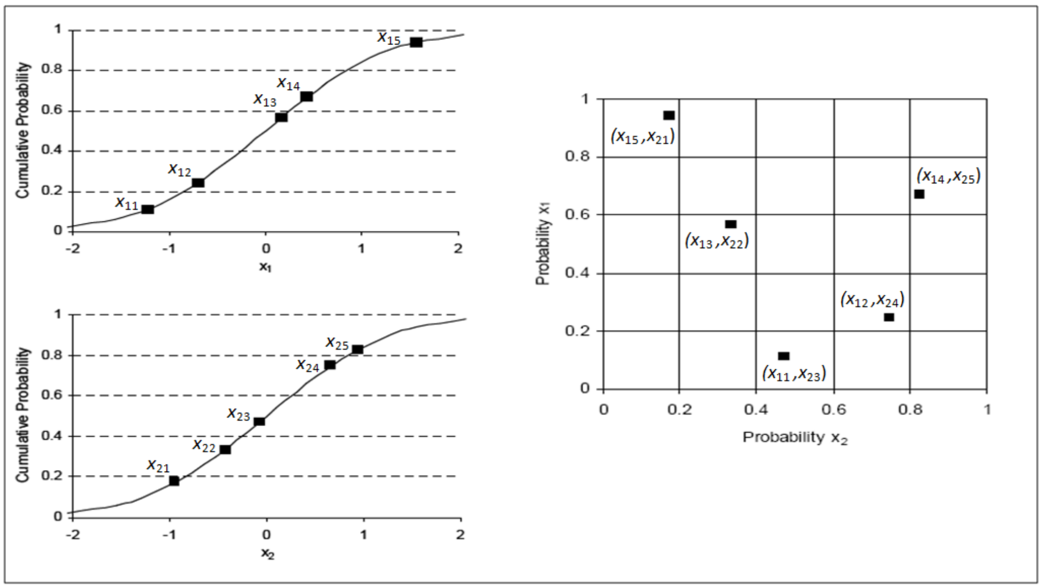


FIGURE 4-1 Example of LHS with Two Variables and Five Intervals

The main shortcoming of the LHS stratification scheme is that "it is one-dimensional and does not provide good uniform properties on a multi-dimensional unit hypercube" (Diwekar, 2003). Moreover, because the elements of each sample are randomly selected, the outcome of LHS can be considered only as a probabilistic output. To maintain the uniformity of samples and the approximate accuracy of the outcome, replicated additions of LHS (Helton et al., 2000; Pleming and Manteufel, 2005) were required, with the replicated samples drawn at predetermined bin fractions. However, repeating the LHS procedure may potentially increase the sample size, which is a crucial issue in the application of LHS for TEPUC because of the large amount of computational time required for large transportation networks. Thus, the first and most important questions related to the application of repeated LHS procedure for TEPUC are these: How should one determine the number of bin fractions? How many corresponding sample sizes or additions of LHS are required to produce the desired output accuracy at the minimum level of confidence acceptable to the transportation planner?

The main objective of this chapter is to conduct an in-depth analysis of the accuracy and convergence properties of repeated LHS in order to obtain an efficient sample size for the solution of TEPUC. This is important not only because these random sampling techniques are crucial for solving large-scale probabilistic network assignment problems but also because the results they generate are not well understood. The literature addressing this type of numerical analysis of the performance of random sampling techniques in the context of transportation network problems is scarce. Unnikrishnan et al. (2005) are one of the few research teams that have investigated the efficient use of different sampling techniques for uncertainty analysis in transportation planning. In order to obtain a reliable approximate solution to compare against other sample techniques, they used M batches ($M > 30$) of N realizations, calculated the sample variance of the average expected objective value across all M batches, and used the sample variance to estimate the confidence intervals. However, a detailed description of the selection of an efficient sample size and its relation to the approximation accuracy and convergence properties of repeated LHS under different predetermined bin fractions was not provided (Unnikrishnan et al., 2005). In fact, an analysis of the approximation accuracy and convergence properties will provide valuable insights into the requirements of efficient sample sizes when repeated LHS techniques are applied to TEPUC. Moreover, for evaluating the efficiency of different sampling methods on a small transportation network, MC is generally used as the benchmark because in this situation the large number of realizations required by MC can be accomplished cost effectively. However, it is not practical to use MC for large transportation networks because of the very high computational time requirements. The in-depth investigation of convergence and accuracy characteristics of LHS also offer us a potential alternative as a benchmark for evaluating other sampling techniques for large networks.

The remainder of this chapter is organized as follows. First, a brief review of the TEPUC, including the mathematical formulation, the sampling–average approximation (SAA) algorithm, and the LHS procedure used in this study are provided. Next, the experimental set-up and the general results of the numerical analysis on two test networks are described. The results of these experiments are analyzed, and key insights are provided related to the practical value of the findings for researchers and transportation planners, focusing on the convergence and approximation accuracy properties of LHS. Finally, a summary of the important results, as well as an overview of directions for future research, are provided.

4.2 Proposed Research Methodology

4.2.1 Formulation and SAA Procedure

The traffic assignment formulated by Wardrop (1952) has been widely used under the standard assumption of deterministic origin destination (OD) demand and link capacity conditions. Typically, two types of traffic assignments are performed: user equilibrium (UE), which assumes that users equilibrate such that each takes the shortest path, and system optimum (SO), which estimates link flows based on certain system-wide objectives (e.g., minimization of travel time). From Sheffi (1981), the formulation for each is

$$
\begin{aligned}
& SO:\ \mathrm{Min}\sum_{a} x_a c_a(x_a)\ \text{ or UE: } \mathrm{Min}\int_0^{x_a} c_a(\omega)d\omega \\
& s.t. \\
& \sum_k h_k^{rs} = q_{rs} \qquad \forall \mathrm{r,s} \\
& h_k^{rs} \geq 0 \qquad \forall \mathrm{r,s} \\
& \mathrm{x_a} = \sum_{\mathrm{r}}\sum_{\mathrm{s}}\sum_{\mathrm{a}} \mathrm{h_k^{rs}}\delta_{\mathrm{a,k}}^{\mathrm{rs}}\ \forall a
\end{aligned}
\tag{4-1}
$$

where

q_{rs} = the OD flow from origin *r* to the destination *s*,

h_k^{rs} = the flow on path *k* from *r* to *s*,

$\check{S}_{a,k}^{rs}$ = a binary value indicating that link *a* exists on path *k* between *r* and *s*,

x_a = the flow on link *a*, and

c_a = the cost of link *a*.

Traditionally, a road network's ability to satisfy current and future demands has been evaluated on the basis of deterministic values of the network capacity and the required demand levels. However, for a given time and day, link capacity can be affected by various link states, including accidents or other incidents, inclement weather, or geometric conditions. In general, the link states may be represented in terms of a probability distribution for each link consistent with the subjective definitions provided by the planner.

Incorporating the above link capacity distributions and supposing that there are *m* links in the network, the uncertain capacity parameter vector $\xi = (\xi_1, \xi_2, \cdots, \xi_m)$ can be viewed as a variable vector, with each item ξ_i having a probability distribution of p_i. The following stochastic programming problem is then formulated:

$$
Min\{f(\mathrm{x}) = \mathrm{E}[F(\mathrm{x}, \xi(\omega))]\} \tag{4-2}
$$

Where $F(x,\xi)$ is the objective function that will derive the traffic assignment toward either SO or UE, and $\xi(\omega)$ is the link capacity, a random vector calculated on the basis of certain probability distributions. The objective function is the expected value of either the SO or UE function, considering the combination of all the "potential" realistic link capacities. The above formulation can also be considered as a bi-level programming formulation, with the upper level being the minimization formulation shown in Equation 3-2 and the lower level being one of the standard traffic assignment formulations shown in Equation 3-1.

To solve the stochastic programming problem shown in Equation 3-2, a common approach is to replace the probability distribution of $\xi(\omega)$ by finite supported measures; that is, $\xi(\omega)$ has a finite number of K possible realizations, called scenarios $(\xi_1,\xi_2,\ldots,\xi_K)$, each with respective probabilities $p_i \in (0,1), i=1,2,\ldots,K$. Supposing that such scenarios can be generated with the same probability, then the expected value function in Equation 3-2 can be written as the finite sum of the outcome of these scenarios as follows:

$$Min\{\hat{f}_k(x) = K^{-1}\sum_{k=1}^{K} F(x,\xi_k)\} \tag{4-3}$$

where $F(x,\xi)$ is the optimal value of either the SO or UE problem, and ξ_k denotes the link capacity vector. For any fixed $x \in X$, $\hat{f}_k(x)$ is an unbiased estimator of the expectation $f(\mathrm{x})$, K is the sample size, and by the Law of Large Numbers, $\hat{f}_k(x)$ converges to $f(\mathrm{x})$ when $K \to \infty$.

For practical implementations on large transportation networks with a large number of scenarios, sampling techniques should be used to randomly select subsets of the set $(\xi_1,\xi_2,\cdots,\xi_k)$ to obtain approximate solutions. This approximate objective, known as an SAA of $f(\mathrm{x})$, is then minimized using a deterministic optimization algorithm. This study used a sampling approach involving LHS, in which a sample was selected from $(\xi_1, \xi_2, \cdots, \xi_k)$ by LHS and a corresponding approximation to $F(x)$ was defined from this sample.

4.2.2 Latin Hypercube Sampling

Let's denote a transportation network as $\mathrm{G(N, A)}$, where N is the set of nodes and A is the set of network links. For each LHS procedure, the number of bin fractions is predetermined. For each link, capacity realizations are generated from each of the bin fractions. These capacity realizations are combined in a random manner to form *m* capacity realizations to be used by LHS. For any two links, the random samples are combined in a manner such that each row and each column has exactly one capacity realization. The algorithm for the LHS in this study is shown below.

Step 1. For a network $\mathrm{G(N, A)}\mathrm{G(N, A)}$, suppose the required number for the sample size is *K*. For each link, divide the link's $(i \to j)$ capacity range into a certain number (*n*) of bin fractions. The values of the capacity realizations are stored in an array $C_{ij}[x]$ $\mathrm{C_{ij}[x]}$, where $i \in N, j \in N, i \neq j;$ x is the index where $x = 1, 2, \ldots, n.$

Step 2. Combine the elements of the sorted arrays for each link capacity based on the indexes in order to generate *m* capacity realizations (C^w $\mathrm{C^w}$), where $w = 1, 2, \ldots, n.$

$$C^w = \{C_{ij}[w]\}, i \in N, j \in N, i \neq j \tag{4-4}$$

Step 3. Record UE or SO objective values for each capacity realization. When the sample size is satisfied, stop sampling and calculate the average UE or SO objective value as the approximated value. Otherwise, repeat the LHS until the sample size is satisfied.

For evaluating the impact of bin fractions and sample size on the convergence and approximation accuracy of LHS, the number of bin fractions can be changed, Steps 1 through 3 can be repeated, and the corresponding approximated value can be calculated. The detailed solution steps for LHS based on the SAA employed in this study can be seen in FIGURE 4-2, where p is the number of times that LHS is repeated and i is the i^{th} sampled capacity realization for each LHS procedure.

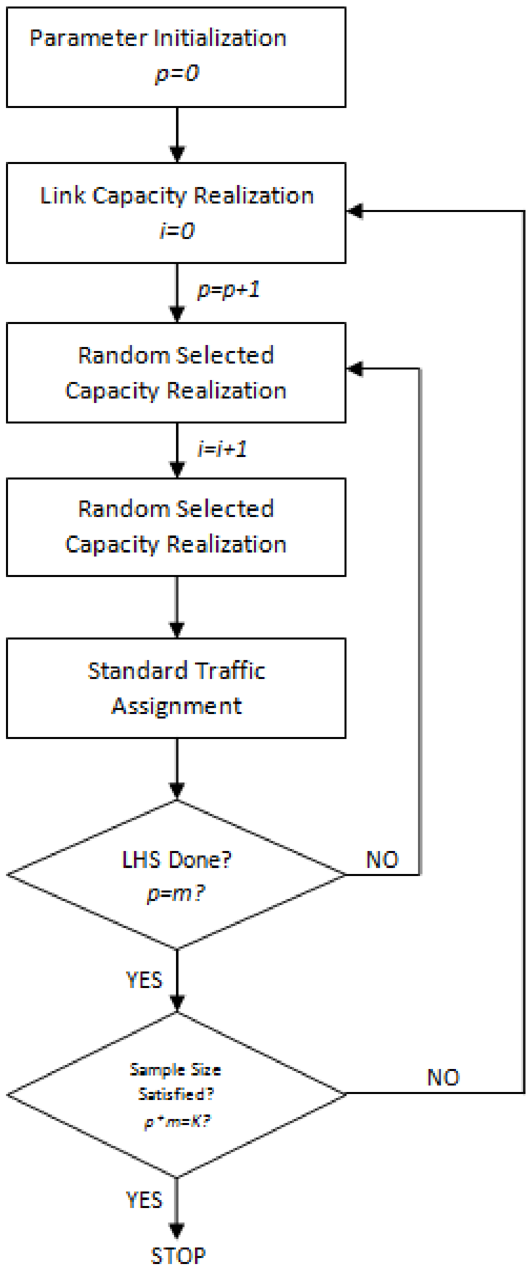


FIGURE 4-2 Flowchart of Repeated LHS-based SAA Solution Steps

4.3 Numerical Experiments and Analysis

This section briefly describes the numerical experiments and performance measures employed for evaluating the convergence and approximation accuracy of LHS for TEPCU. In this study, a small test network and the Nguyen-Dupuis network are used. The test network has four nodes, five links, and one OD pair; the Nguyen-Dupuis network has 13 nodes, 19 links, and four OD pairs. Detailed network information can be found in Appendix A.

Recent studies (Brilon et al., 2005; Ozguven and Ozbay, 2008) indicated that the Weibull distribution was the best fit for capacity distribution based on the censored highway traffic data. Thus, in all scenarios of this study, the link capacity was assumed to be Weibull distributed. The demand was assumed to be fixed. According to the solution steps given in FIGURE 4-2, each sample with a specific capacity realization was updated in the standard traffic assignment formulation shown in Equation 3-1. In this study, the Frank Wolf algorithm was used to solve the standard traffic assignment problem obtained as a result of each capacity realization.

4.3.1 Performance Measures

Two performance measures used in Unnikrishnan et al. (2005)—namely, error of the estimate and approximation accuracy—were used in this study for evaluating the convergence and approximation accuracy.

4.3.1.1 Error of the Estimate

The standard error of a method of measurement or estimation is "the standard deviation of the sampling distribution associated with the estimation method" (Everitt, 2002). In other cases, the standard error may be used to provide an indication of the size of the uncertainty. The error of the estimate in this study is defined as the length of the interval on either side of the estimate within which the true mean is expected to lie with 95% confidence. The error is defined as

$$Error = 1.96 * \frac{S}{\sqrt{K}} \tag{4-5}$$

where

S = the sample standard deviation, and

K = the sample size.

4.3.1.2 Accuracy of Approximation

The accuracy of approximation is defined as the percentage variation of the estimate from the "true" expected value. This is a measure of how far the estimate is from the closest approximation that can be found with substantially greater sampling. In this chapter, the true expected value is approximated by the benchmark obtained by running the MC algorithm for 100,000 capacity realizations.

$$Accuracy = \left| \frac{\bar{f}_K - f^*}{f^*} \right| \tag{4-6}$$

where

$\bar{f}_K$ = the expected value of K sample size, and

f^* = the value of the benchmark.

4.3.2 Computation Results and Analysis

4.3.2.1 Required Sample Size for the Convergence of LHS

As noted earlier, the property of convergence is beneficial for comparing the approximation accuracy of output results at a given level of confidence. The convergence of LHS is dependent on the sample size with different predetermined bin fractions. In this chapter, the link capacity distribution was divided into a different number of bin fractions for both the test network and the Nguyen-Dupuis network. The error of the estimate was employed to evaluate the convergence property of LHS. For each predetermined number of bin fractions, 10,000 samples were generated, and the error of the estimate of the TEPCU objective function was summarized with respect to the different number of bin fractions and sample sizes shown in TABLE 4-1 and TABLE **4-2**. FIGURE 4-3 shows how the error of the estimate was affected by the increase in the sample size with different predetermined bin fractions. It was observed that for both networks, the convergence rate was related only to the sample size and that there was no significant difference among the different number of bin fractions. When the sample size was increased, the error of the estimate decreased, and the convergence rate gradually slowed down. The inflection point of the curve shown in FIGURE 4-3 (i.e., the point where the slope of the curve changed from sharp to flat) is between 500 and 2,000 sample sizes. In other words, the error of the estimate decreased very slowly when the sample size was more than 2,000.

TABLE 4-1 Error of the Estimate of TEPUC Objective Function (Test Network)

Number of bin fractions	**Sample sizes**						
	100	400	1,000	2,000	4,000	6,000	10,000
50	21.7065	11.2095	7.00157	4.96799	3.50303	2.86766	2.22375
100	23.4844	12.0976	7.70040	5.35662	3.80307	3.09814	2.40078
200	-	13.4018	8.04631	5.6336	3.90484	3.14663	2.44498
500	-	-	8.0722	5.72590	4.0332	3.30587	2.53311
1,000	-	-	8.3953	5.74905	4.08133	3.32017	2.54475

TABLE 4-2 Error of the Estimate of TEPUC Objective Function (ND Network)

Number of bin fractions	**Sample sizes**						
	100	400	1,000	2,000	4,000	6,000	10,000
50	10.0376	5.84018	3.72564	2.70377	1.89242	1.54106	1.18745
100	12.4470	5.81760	3.77361	2.68714	1.88299	1.55430	1.21060
200	-	6.34698	3.90432	2.72372	1.92424	1.56955	1.21731
500	-	-	3.99270	2.80433	1.99379	1.6248	1.24838
1,000	-	-	3.93709	2.7704	1.95707	1.60012	0.87992

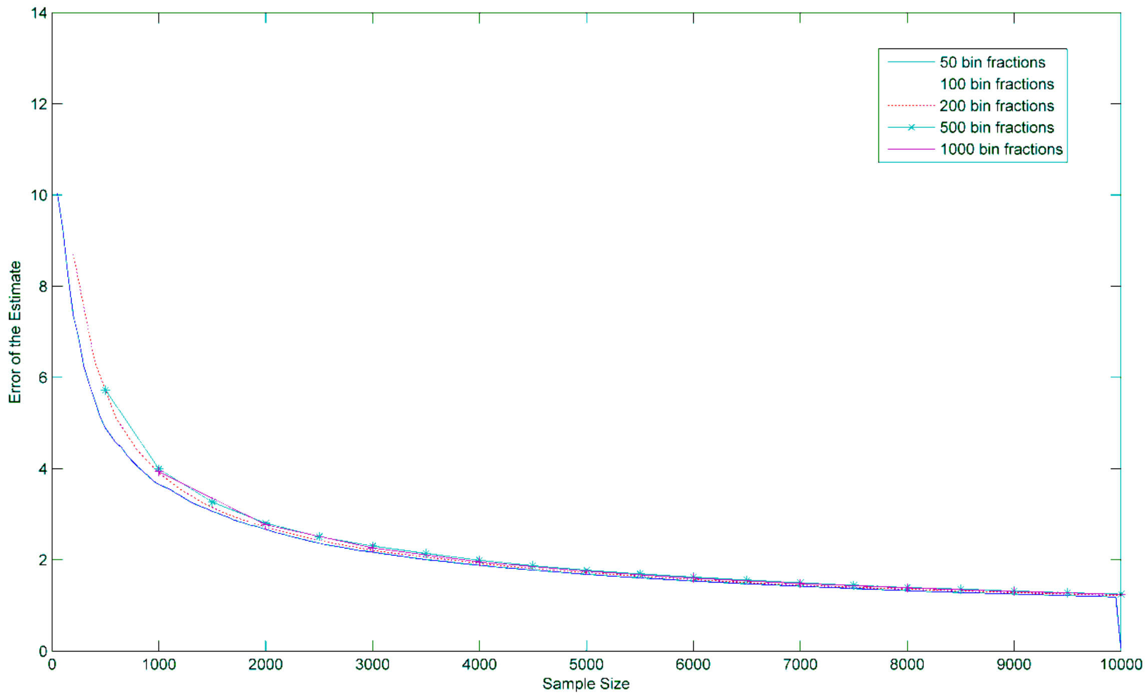


FIGURE 4-3 Error of the Estimate for Different Bin Fractions and Sample Sizes (Nguyen-Dupuis Network)

4.3.2.2 Approximation Accuracy of LHS

Earlier in this chapter, "approximation accuracy" was defined as the percentage variation of the estimate from the benchmark value. A smaller accuracy value indicates better approximation accuracy. The main goal of this chapter is to determine the relationship between approximation accuracy and sample size under different predetermined numbers of bin fractions. The results of this investigation are summarized in TABLE 4-3 and

TABLE **4-4** and FIGURE 4-4. For both test networks with predetermined numbers of bin fractions, it was observed that the value of approximation accuracy consistently decreased when the sample size increased. In FIGURE 4-4, it was observed that the value of approximation accuracy became stable when the sample size was larger than 2,000. Moreover, it was observed that the predetermined number of bin fractions had a significant effect on the approximation accuracy. For the same sample size, when the number of bin fractions increased, the value of approximation accuracy improved. However, the approximation accuracy did not change when the number of bin fractions was large. For example, in FIGURE 4-4, there is no obvious difference between accuracy value samples with 500 and 1,000 bin fractions. From another perspective, the results also indicate that the worst-case scenario for LHS application occurs when there is a small number of bin fractions (e.g., 50 or 100) and a limited sample size (e.g., smaller than 500). The approximation result is neither stable nor accurate compared to functions performed with a larger number of bin fractions.

TABLE 4-3 Approximation Accuracy of TEPUC Objective Function (Test Network)

Number of bin fractions	Sample sizes						
	100	400	1,000	2,000	4,000	6,000	10,000
50	1.30E-02	1.26E-02	1.26E-02	1.24E-02	1.25E-02	1.25E-02	1.25E-02
100	7.28E-03	7.24E-03	7.09E-03	7.53E-03	7.20E-03	7.37E-03	7.35E-03
200	-	3.10E-03	3.77E-03	3.80E-03	4.18E-03	4.36E-03	4.30E-03
500	-	-	2.13E-03	2.07E-03	2.04E-03	2.00E-03	2.14E-03
1,000	-	-	1.18E-03	1.42E-03	1.21E-03	1.30E-03	1.42E-03

TABLE 4-4 Approximation Accuracy of TEPUC Objective Function (ND Network)

Number of bin fractions	Sample sizes						
	100	400	1,000	2,000	4,000	6,000	10,000
50	2.62E-03	1.85E-03	1.95E-03	1.76E-03	1.80E-03	1.70E-03	1.74E-03
100	8.83E-04	1.66E-03	1.05E-03	1.16E-03	1.22E-03	1.05E-03	1.02E-03
200	-	7.95E-04	8.26E-04	6.86E-04	7.12E-04	6.82E-04	5.83E-04
500	-	-	6.44E-04	1.83E-04	1.56E-04	4.72E-05	1.20E-04
1,000	-	-	2.22E-04	6.47E-05	2.27E-04	2.49E-04	2.69E-04

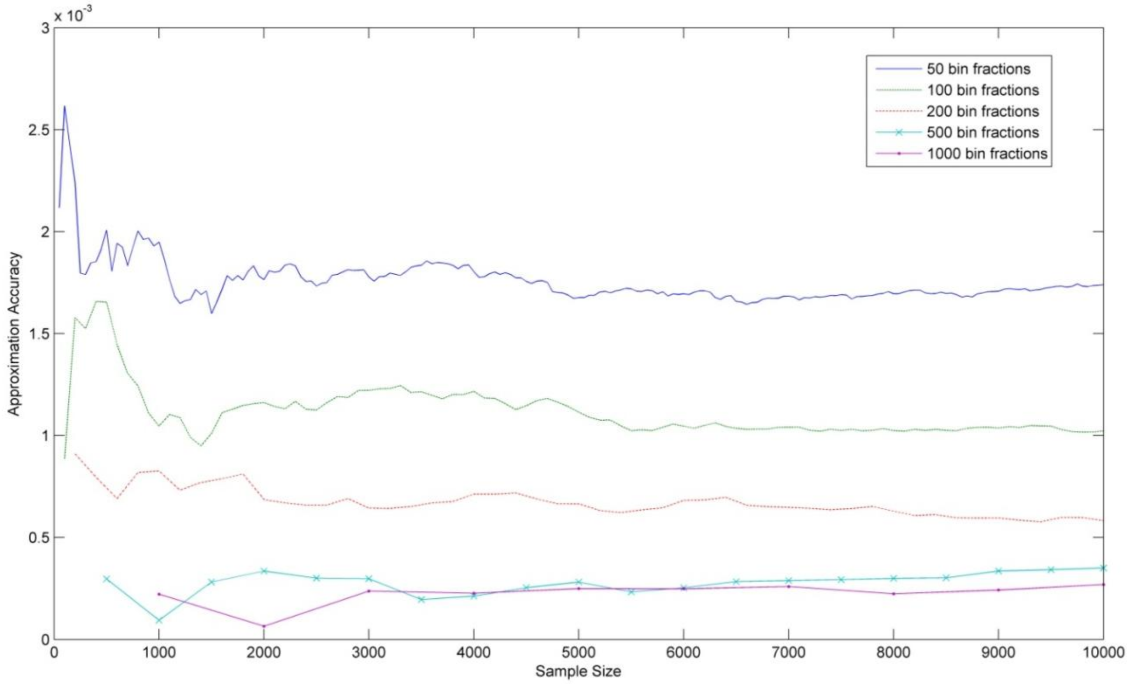


FIGURE 4-4 Approximation Accuracy for Different Bin Fractions and Sample Sizes (ND Network)

4.3.2.3 Comparison of Performance of LHS and MC

In this chapter, we compared the approximation accuracy of LHS and MC using a Nguyen-Dupuis network. The results shown in FIGURE 4-5 agree with those found in previous studies (Lemieux, 2009), indicating that "due to relative high variance of output results, MC can only be applied with a large number of sample size for obtaining an accurate and stable result." However, in cases dealing with large transportation networks, it is not practical to have very large sample sizes (e.g., 100,000), mainly because of the high computational time requirements. In FIGURE 4-5, it can be observed that using LHS, the output results quickly converged and became stable when an acceptably small sample size was used and when the number of bin fractions was large. This represents a significant advantage over MC. Although the approximation accuracy of LHS is slightly worse than that of MC, this can be considered a compromise between the approximation accuracy and computational time requirements. Moreover, the positive convergence and approximation accuracy properties of LHS for TEPCU also make it a good candidate as a benchmark for evaluating other sampling techniques for the large transportation networks.

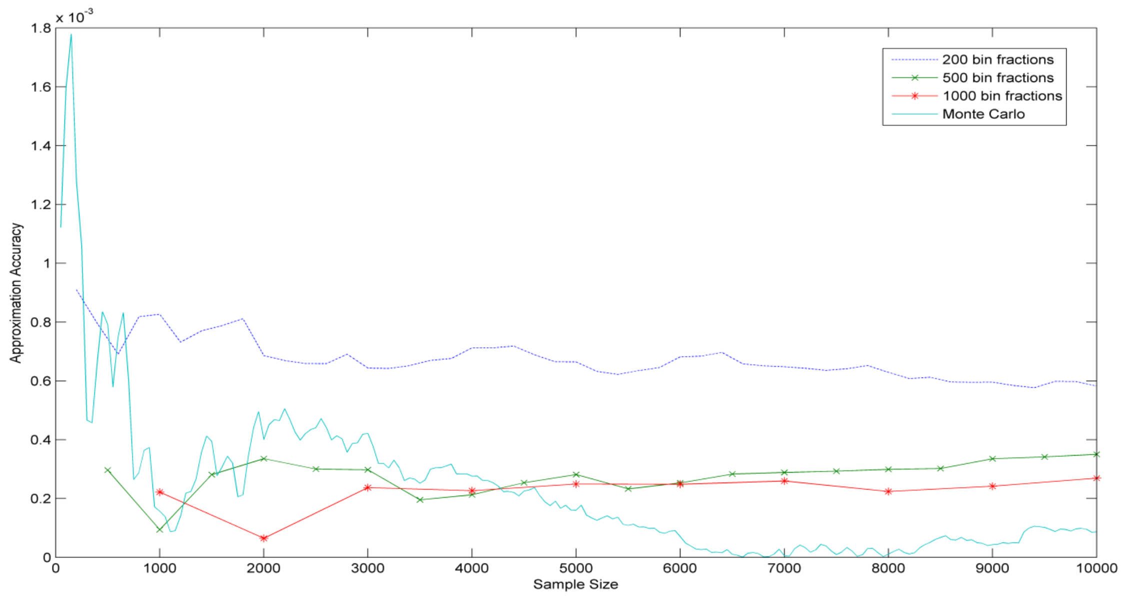


FIGURE 4-5 Approximation Accuracy of LHS and MC for Different Bin Fractions and Sample Sizes (ND Network)

4.4 Summary

This chapter investigated the convergence and approximation accuracy properties of LHS for TEPUC. In order to evaluate the results with respect to approximation accuracy at a sufficient level of confidence, this chapter investigated the impact of sample sizes with a different number of bin fractions on accuracy. Two performance measures—error of estimate and approximation accuracy—were employed, and two test networks were used. The results indicate that the convergence rate was related only to the sample size and that no significant difference was observed as a result of the differences in the size of the predetermined bin fractions. When the sample size was increased, the error of the estimate decreased and the convergence rate gradually slowed down. Moreover, it was observed that the predetermined number of bin fractions had a significant effect on approximation accuracy. For the same sample size, when the number of bin fractions increased, the value of approximation accuracy improved. However, the approximation accuracy exhibited a stable trend when the number of bin fractions was large. These results provide important information that can help to set up a proper experimental design for LHS applied to TEPUC. When a sufficiently large number of bin fractions is combined with a proper sample size, it is possible to obtain a highly accurate approximate result at a high level of confidence.

Primarily because of computational time limitations, this chapter investigated only two test networks. The results of both of these investigations were checked for consistency. In the future, it will be beneficial if the methodology and procedure used in this chapter can be applied to other networks and compared with the results of this chapter. Another area of potential research is to test other suitable sampling techniques for larger transportation networks using the results of LHS as the benchmark. Until now, all the tests and evaluations reported in the literature have been based on small networks. It will be interesting to evaluate whether other sampling techniques that are suitable for small networks may also be applicable to a larger and more realistic network.

5 CASE STUDY: LINK CRITICALITY EVALUATION IN DEGRADABLE TRANSPORTATION NETWORKS

Link criticality evaluation is an important problem for public officials engage in hazard mitigation planning. This chapter proposes an analytical framework and an efficient solution procedure for link criticality evaluation, which considers the impact of day-to-day degradable transportation network conditions. This is in fact an extension of the analysis approach provided in chapter 4 by using the LHS sampling solution approach of the probabilistic traffic assignment formulation to determine and rank critical links.

In this chapter, link capacity is considered a multi-status variable, and a sampling technique is used to generate realizations of transportation network capacity values. With different capacity realizations, traffic demand is repeatedly assigned on the regional planning model network, and the assignment results are measured with multiple criteria and analyzed using several statistical indices. A case study based on a portion of the New Jersey roadway network is presented to verify the proposed approach.

5.1 Introduction

Identification of the critical links in a transportation network is an important part of transportation network vulnerability analysis. This problem is concerned with finding the links that result in severe deteriorations of network performance (e.g., total user travel time) when degradable. In the case of a specific application for transportation facilities assessment, most studies use an enumeration method (complete sampling) that sets scenarios that each assume a certain link is degradable. The links that cause severe network performance deteriorations are identified as critical links.

When considering link degradation levels, past studies normally assume binary status: fail or not. This assumption is reasonable under emergency situations, such as earthquakes or hurricanes; however it is not suitable for daily traffic conditions (Sullivan et al., 2010). Daily uncertain events may simultaneously result in different links degrading at multiple levels. In other words, the operational capacity of a link is a continuous status, and degradation might happen simultaneously for different links under daily transportation network conditions. Thus, it is necessary to adopt a more practical approach to capture link criticality for day-to-day degradable transportation networks due to the occurrence of various hazard events.

The main objective of this study is to detect and rank critical links considering degradable transportation networks under the risks of daily hazard events. We propose an analytical framework incorporating realistic, risk-related data sets with a regional transportation planning model. In order to represent day-to-day transportation network conditions, the traditional regional planning model is extended by considering link capacities as variables with certain distributions. The distributions of link capacities are calculated through the combination of frequency of risks and corresponding roadway capacity reductions. For link criticality analysis, firstly, we repeatedly run the traffic assignment procedure in the regional planning model with different network capacity realizations. Then, a GIS-based interactive computer tool, developed for the evaluation and analysis of full cost of highway transportation, is used to calculate total system cost. Finally, based on the calculated costs, the critical links are detected and ranked in terms of following statistical indices: rank correlation coefficients (RCCs), standardized rank regression coefficients (SRRCs), and partial rank correlation coefficients (PRCCs).

Several features distinguish this study from previous ones. Firstly, the roadway capacities in degradable transportation networks are considered multi-status but not binary status as in previous studies. Through a sampling technique, each sample realization can be interpreted as one daily network capacity condition. Secondly, we measure the total cost with different performance measures via a GIS-based interactive computer tool that calculates total network travel costs not general total system travel time. Finally, three statistical indices are used for measuring criticality in this study instead of the Volume-to-Capacity ratio (V/C). V/C ratio is commonly used as a criticality measure with a full-capacity assumption. However, when considering daily hazard events, it is not a proper measure due to day-to-day dynamic transportation network conditions.

5.2 Literature Review

The problem addressed in this study is related to previous theoretical work on the most vital arc or edge problem. In detail, the problem is finding the arc or edge that on its removal results in maximum deterioration of network performance. The solution methods include graph theory and game theory. In graph theory, a general performance measure can be the increase of shortest path length (Malik et al., 1989; Ball et al., 1989). The studies formulated the most vital arcs problem as determination of the subset of arcs whose removal from the network resulted in the greatest increase in the shortest path length. The measure of the performance of a network in Barton (2005) was the increase in the distance between the origin nodes and sink nodes in a maximum flow graph. While game theory approach (Bell 1999) is considered the situation where a network "spoiler" seeks to disrupt the network to maximize user costs by choosing the link that causes the maximum impact, users try to minimize their costs by adjusting their routes according to the expected link costs. The results of the game were therefore worst-case link failure probabilities, which could be used to find the upper-bound impact of link degradation. Applications of this approach were described in Cassir (2001) and Cassir et al. (2003).

For the specific application of the assessment of transportation facilities, most studies use bilevel formulations to solve the problem: at the lower level to assign vehicles to achieve the goal of user equilibrium or system optimality and at the upper level critical links that maximize network performance deteriorations as a result of their removal. The procedure mainly relates to three issues: the assignment methodology, performance measure, and decision support systems (DSS).

The assignment methodology can be generally categorized as either static or dynamic traffic assignment. Static assignment assumes that traffic is in a steady status, and the time to traverse a link depends only on the number of vehicles on that link. Because of its simple mathematical formulation and solution procedure, static assignment is widely applied for link criticality evaluation on a regional network scale. Dynamic assignment can successfully represent the time-varying nature of the congestion during different times of the day and help to explain travelers' responses to time-varying transportation system operations. However, compared with static assignment, dynamic assignment requires more data support and computation costs. Thus, dynamic assignment is more suitable for evaluating simple networks or arterial analysis considering users' behavior.

Performance measures can be separated into two categories: accessibility and economic measures. Accessibility refers to the ease of reaching opportunities for activities and services and can be used to assess the performance of an urban transportation system (Chen et al., 2007; Jenelius et al., 2006; Taylor, 2008). Economic measures refer to the cost of disruption due to the degradable critical links, such as travel time (Murray-Tuite and Mahmassani, 2004; Ukkusuri and Yushimito 2009; Scott et al., 2006; Tampere et al., 2007; Nagurney and Qiang, 2008; Qiang and Nagurney, 2008), environment (Nagurney and Qiang, 2010), and network efficiency

(Nagurney and Qiang, 2008). In detail, alternative definitions and measures are summarized in (Nicholson, 2003; Sullivan et al., 2009*).*

DSSs, based on multi-criteria measures in transportation infrastructure evaluation, have been investigated in various areas, such as infrastructure maintenance and management (Jha, 2003; Chou et al., 2007), highway safety and incident/accident management (Borne et al., 2003; Chassiakos et al., 2005). The common features in the previous DSS can be categorized as follows: the characteristics of uncertainties, performance measure, qualitative nature of subsystem components, and general system size. Because of system complexity and insufficient dataset, knowledge-based expert systems are commonly used for optimized solutions. A recent application of DSS in critical civil infrastructure management for disasters can be seen in Croope (2010).

5.3 Research Methodology

5.3.1 Mathematical Formulation

The general procedure of a regional transportation planning model includes four steps: trip generation, trip distribution, model split, and traffic assignment. Through the first three steps, the total number of travelers for each transportation mode (auto, transit, etc.) can be predicted. Static traffic assignment can then be used to assign the predicted demand onto the transportation network. In static traffic assignment, traffic demand between origins and destinations is generally assumed as an input from the previous three steps.

Static traffic assignment has found significant applications since Wardrop (1952). Typically, two types of traffic assignment can be performed: user equilibrium (UE), which assumes that users reach equilibrium when they cannot improve their travel time by switching to alternate routes, and system optimum (SO), which estimates link flows based on some system-wide objective (e.g., minimization of travel time). This static network analysis is generally based on mean values, such as travel time, travel distance, or level of congestion. However, for the critical link analysis under the assumption of the possibility of certain types of disasters, a probabilistic approach is needed. From Sheffi (1981) the "deterministic" formulation was given in the previous section. For completeness purposes, we list the formulation as follows:

$$
\begin{aligned}
&SO:\ \mathrm{Min}\sum_a x_a c_a(x_a)\ \text{ or UE: } \mathrm{Min}\int_0^{x_a} c_a(\omega)d\omega \\
&s.t. \\
&\sum_k h_k^{rs} = q_{rs} \qquad \forall \mathrm{r,s} \\
&h_k^{rs} \geq 0 \qquad \forall \mathrm{r,s} \\
&\mathrm{x_a} = \sum_{\mathrm{r}}\sum_{\mathrm{s}}\sum_{\mathrm{a}} \mathrm{h_k^{rs}} \delta_{\mathrm{a,k}}^{\mathrm{rs}}\ \forall a
\end{aligned}
\qquad (5\text{-}1)
$$

Where q_{rs} is the OD flow from origin r to the destination s, h_k^{rs} is the flow on the path k from r to s, $\delta_{\mathrm{a,k}}^{\mathrm{rs}}$ is a binary value indicating that link a exists on path k between r and s, x_a is the flow on link a, and c_a is the cost of link a.

Traditionally, the adequacy of a road network is evaluated based on deterministic network capacity and origin-destination demands. In order to model the impact of uncertain events on link capacity, sensor data can be used (Ozguven and Ozbay 2008). When sensor data are unavailable, the link status may be represented by a theoretical probability function of the following form:

$$C_{ir} = f(S_{i1}, S_{i2}, \ldots, S_{im}) \qquad (5\text{-}2)$$

Where C_{ir} is the real capacity of link i in the presence of certain uncertain event—namely, $S_{i1}, S_{i2}, \ldots, S_{im}$. For example, considering accidents and extreme weather conditions, the link capacity can be simply represented as follows:

$$C_{ir} = (1-\alpha_{ia})(1-\alpha_{iw})C_i \tag{5-3}$$

Where C_i is the recommended link capacity value in HCM 2000, and α_{ia} and α_{iw} are capacity reduction coefficients of accident and weather status, respectively. The link capacity distribution can be obtained by repeatedly calculating equation (5-3) for different days.

5.3.2 Sampling-Based Method

Suppose for a network with m links, the network capacity can be formulated as a variable vector $\xi = (\xi_1, \xi_2, \ldots, \xi_m)$. Each item ξ_i represents a certain link capacity with a probability distribution p_i. We can generate a network capacity as a variable vector with certain realizations and then propagate the samples through the analysis to produce the mapping $[\xi, F(x,\xi)]$. F is the measure function, such as objective function in Equation 5-1. However, the mapping procedure is usually the most computationally demanding part of a sampling-based uncertainty and sensitivity analysis. For example, in a network with 200 links and three-link status, the total number of scenarios is 3^{200}. It is not thus computationally possible to solve the formulation given in Equation 5-1 for all capacity realizations.

However, we can use variance reduction sampling techniques (Helton and Davis, 2003) to obtain approximate solutions by selecting subsets of the set $(\xi_1, \xi_2, \ldots, \xi_k)$. This approximate solution approach, known as a sample average approximation (SAA) of $f(\mathrm{x})$, is then minimized by using a deterministic optimization algorithm. The detailed steps of the SAA technique employed in this study can be seen in FIGURE 5-1. The detailed behavior of this technique and its application can be seen in Helton and Johnson (2006) and Helton and Davis (2003).

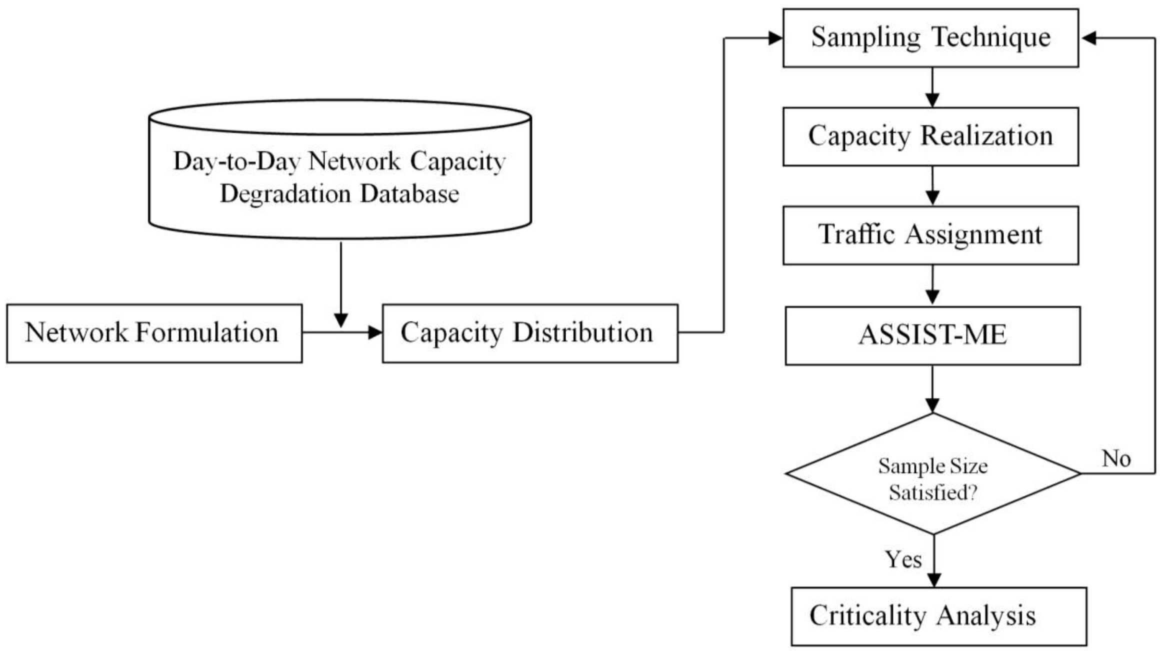


FIGURE 5-1 Representation of SAA Solution Steps

It should be noted that because static assignment is used for each realization of capacity reduction, it assumes that users have perfect information about the current network condition. Moreover, although in reality it may depend on network topology (e.g., series or parallel links), the capacity of any pair of links are assumed to be independently distributed in this study. Our consideration is that the proposed framework is mainly used for regional planning. The mathematical formulation, data collection process, and analysis are all on a macroscopic level. In addition, the incorporation of link correlation in the proposed framework may bring more questions, such as how many upstream links need to be considered and how to set all the values of degradable factors for all those links. Currently, macroscopic data are not sufficient to answer such questions.

5.3.3 GIS-Based Multi-criteria Cost Estimation Tool

The GIS-based multicriteria cost estimation tool, which is named Advanced Software for Statewide Integrated Sustainable Transportation System: Monitoring and Evaluation (ASSIST-ME), is a computer program developed by Ozbay et al. (2009). ASSIST-ME employs ArcGIS in the Visual Basic .NET environment to visualize and process a very large amount of model and sensor data for a given transportation network. It calculates direct and indirect transportation-related link-based or OD-based trip costs using the output of the regional planning model. The OD-based trip cost is calculated using the constrained *k* shortest-path algorithm implemented in the C programming language. Link-based costs are calculated for a selected region (e.g., county) or network wide. In order to calculate the total network costs, the link-based cost estimation functionality of ASSIST-ME is used in this study.

The cost categories used in this study are vehicle operation, travel time and congestion, accident, air pollution, noise, and maintenance costs. Each cost function was estimated (Ozbay et al., 2007; Berechman et al., 2011) using data obtained from the New Jersey Department of Transportation (NJDOT) and other state and national sources. These cost functions are presented in TABLE 5-1. It should be noted that data on vehicle operation cost, accident cost, and infrastructure cost are New Jersey-specific, whereas congestion and environmental costs are adopted from relevant studies in the literature. The parameters of the cost functions are modified to reflect New Jersey-specific conditions.

TABLE 5-1 Cost Function in ASSIST-ME (Ozbay et al., 2007)

<table>
<tr><th>Cost</th><th colspan="2">Cost function</th><th>Variable definition</th></tr>
<tr><td>Operation</td><td colspan="2">$C_{opr} = 7208.73 + 0.12(m/a) + 2783.3a + 0.143m$</td><td>$a$: vehicle age (years); m: vehicle mileage (miles)</td></tr>
<tr><td>Congestion</td><td colspan="2">$C_{opr} = \begin{cases} Q\frac{d_{a,b}}{V_0}(1+0.15(\frac{Q}{C})^4)VOT & ifQ \le C \\ Q\frac{d_{a,b}}{V_0}(1+0.15(\frac{Q}{C})^4)VOT + Q(\frac{Q}{C}-1)\frac{VOT}{2} & ifQ > C \end{cases}$</td><td>$Q$: volume (veh/day); $d_{a,b}$: distance (mile); C: capacity (veh/hr); VOT: value of time (\$/hr); V_0: free flow speed (mph)</td></tr>
<tr><td rowspan="3">Accident</td><td>Category 1: Interstate-freeway</td><td>$C_{acc} = 127.5Q^{0.77}M^{0.76}L^{0.53}$
$+114.75Q^{0.85}M^{0.75}L^{0.49}$
$+198{,}900Q^{0.17}M^{0.42}L^{0.45}$</td><td rowspan="3">$Q$: volume (veh/day); M: path length (miles), L: number of lanes</td></tr>
<tr><td>Category 2: Principal arterial</td><td>$C_{acc} = 178.5Q^{0.58}M^{0.69}L^{0.43}$
$+18{,}359Q^{0.45}M^{0.63}L^{0.47}$</td></tr>
<tr><td>Category 3: Arterial-collector</td><td>$C_{acc} = 229.5Q^{0.58}M^{0.77}L^{0.77}$
$+9{,}179.96Q^{0.74}M^{0.81}L^{0.75}$</td></tr>
<tr><td>Air pollution</td><td colspan="2">$C_{air} = Q(0.01094 + 0.2155F)$ $where;$
$F = 0.0723 - 0.00312 + 5.403 \times 10^{-5}V^2$</td><td>$F$: fuel consumption (gl/mile); V: average speed (mph); Q: volume (veh/hr)</td></tr>
<tr><td>Noise</td><td colspan="2">$C_{noise} = 2\int_{r_1=50}^{r_2=r_{\max}} (L_{eq}-50)DW_{avg}\frac{RD}{5280}dr$
$where;$
$K = K_{car} + K_{truck}$
$K = \frac{F_c}{V_c}(V_c^{4.174}10^{0.115} + 10^{5.03F_{ac}+(1-F_{ac})6.7})$
$+\frac{F_{tr}}{V_{tr}}(V_{tr}^{3.588}10^{2.102} + 10^{7.43F_{atr}+(1-F_{atr})7.4})$
$L_{eq} = 10\log(Q) + 10\log(K) - 10\log(r) + 1.14$</td><td>$Q$: volume (veh/hr); RD: residential density (units/mile^2); D: percentage discount in value per increase; W_{avg}: average housing value; r: distance to highway; K: noise-energy emission; K_{car}: auto emission; K_{truck}: truck emission; F_c: % of autos; F_{tr}: % of trucks; F_{ac}:% of const. speed autos; F_{atr}: % of const. speed truck; V_c: auto speed (mph); V_{tr}: truck speed (mph); L_{eq}: equivalent noise level.</td></tr>
<tr><td>Maintenance</td><td colspan="2">$\ln(C_r) = -0.716 + 0.8197\ln(N \cdot L_m)$</td><td>$C_r$: resurfacing cost; N: number of lanes; L_m: length of project (miles)</td></tr>
</table>

5.3.4 Sensitivity Analysis

5.3.4.1 <u>Rank Transformation Technique</u>

A number of statistical indices that can be used along with the SAA procedure are briefly summarized in Helton and Johnson (2006). For a linear relationship, the common statistical indices are correlation coefficients (CC), standardized regression coefficients (SRC), and partial correlation coefficients (PCC). All three indices can provide a criticality strength of linear relationship between ξ and $F(x,\xi)$. For capturing a nonlinear relationship, rank transformation (Satelli and Sobol, 1995) is a well-known technique proved to perform efficiently by Helton and Johnson (2006). By using rank transformation, input data ξ and the output result $F(x,\xi)$ are replaced with their corresponding ranks so that the linear relationship measures can be used. For each capacity realization ξ_{ij}, i is the sample number and j is the link number. An example rank transformation scheme can be seen in FIGURE 5-2. A detailed discussion about rank transformation in the context of sensitivity analysis can be found in Satelli and Sobol (1995).

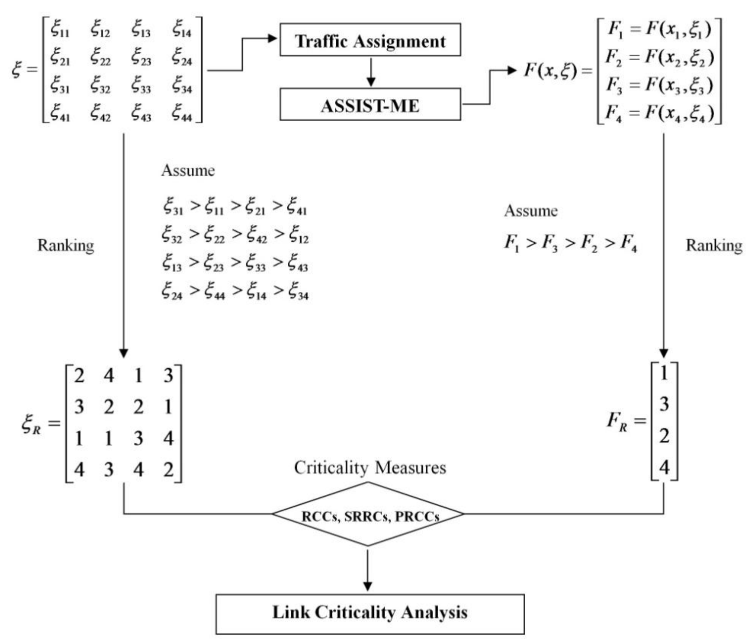


FIGURE 5-2 Rank Transformation Technique with Criticality Measures

5.3.4.2 Criticality Measures

In this study, sensitivity results obtained based on the following criticality measures borrowed from Helton and Johnson (2006) are illustrated and compared. These are rank correlation coefficients (RCCs), standardized rank regression coefficients (SRRCs), and partial rank correlation coefficients (PRCCs).

RCCs

RCC provides a measure of the strength of the linear relationship between ranked ξ and $F(x,\xi)$. The measure can be mathematically expressed as follows:

$$c(\xi_j, F) = \frac{\sum_{i=1}^{m}(\xi_{ij} - \overline{\xi_j})(F_i - \overline{F})}{[\sum_{i=1}^{m}(\xi_{ij} - \overline{\xi_j})^2]^{1/2}[\sum_{i=1}^{m}(F_i - \overline{F})^2]^{1/2}} \tag{5-4}$$

Where $\overline{\xi_j} = \sum_{i=1}^{m}\xi_{ij} / m$ and $\overline{F} = \sum_{i=1}^{m} F_i / m$, m is the sampling size.

SRRCs

Regression analysis in this study is formulated as linear models of the following form:

$$\hat{F} = b_0 + \sum_{j=1}^{m} b_j \xi_j \tag{5-5}$$

The regression coefficients in Equation 5-5 are determined such that the sums of Equations 5-6 and 5-7 are minimized, respectively.

$$\sum_{i=1}^{m}(F_i - \hat{F}_i)^2 = \sum_{i=1}^{m}[F_i - (b_0 + b_j \xi_{ij})]^2 \tag{5-6}$$

$$\sum_{i=1}^{m}(F_i - \hat{F}_i)^2 = \sum_{i=1}^{m}[F_i - (b_0 + \sum_{j=1}^{m} b_j \xi_j)]^2 \tag{5-7}$$

PRCCs

The PRCC equation is related to the RCC equation. Firstly, we formulate two regression models:

$$\hat{\xi}_j = c_0 + \sum_{p=1, p \neq j}^{m} c_p \xi_p \text{ and } \hat{F}_j = b_0 + \sum_{p=1, p \neq j}^{m} b_p \xi_p \tag{5-8}$$

Then use the new variables $\xi_j - \hat{\xi}_j$ and $F - \hat{F}$ to calculate RCC with Equation 5-4. In other words, PRCCs between ξ_j and F is the RCCs between $\xi_j - \hat{\xi}_j$ and $F - \hat{F}$.

5.4 Case Study

5.4.1 Scenario Description

A case study is performed on the network of northern New Jersey. The roadway network includes densely populated, congested locations. The regional planning model, North Jersey Regional Transportation Model-Enhanced (NJRTM-E, 2011), is used to estimate the traffic flows on the network. NJRTM-E is a four-step transportation planning model currently used by the North Jersey Transportation Planning Authority (NJTPA). Four separate networks are run for the time periods in the model: AM peak (6:00 a.m.–9:00 a.m.), midday (9:00 a.m.–3:00 p.m.), PM peak (3:00 p.m.–6:00 p.m.), and night (6:00 p.m.–6:00 a.m.). The model includes a detailed highway network with 6.5 million residents and 23,000 miles of highway network, which includes 2,553 zones, 21,740 nodes, and 43,709 links.

Based on the NJRTM-E model, it is possible to estimate the transportation costs via ASSIST-ME under possible roadway capacities combinations. In this case study, seven major roadways located in Union and Essex counties are selected for analysis in the PM peak time period. The impact of weather and accidents on roadway capacity are considered. Detailed information about roadway sections can be seen in TABLE 5-2.

.

TABLE 5-2 Information for the Roadway Sections

Link no.	Name	County	Road type	Mile post	No. acc*	V/C ratio**
1	I-78	Union, Essex	Interstate highway	55-60	69	1.05
2	U.S. 1&9	Union, Essex	U.S. highway	45-48	33	1.09
3	U.S. 1&9	Union	U.S. highway	42-45	42	0.87
4	I-95	Union	Interstate highway	52-55	51	1.14
5	I-95	Union, Essex	Interstate highway	55-58	30	1.06
6	NJ-27	Union	Regional highway	31-34	68	0.88
7	NJ-27	Union, Essex	Regional highway	34-38	31	0.82

*The value obtained from local transportation agencies (Yazici et al., 2010), PM peak period (3:00 p.m.–6:00 p.m.).
**The value obtained from the result of PM peak period network assignment result in NJRTM-E .

5.4.2 Analysis Approach

One of the most frequently used sampling methods, Latin hypercube sampling (LHS) is used as the sampling technique in SAA. A detailed analysis of the convergence and approximation accuracy properties of LHS can be found in Li and Ozbay (2010). The full costs calculated by ASSIST-ME are used as the performance measure. The general steps of the proposed methodology are as follows:

Step1: Collect historical weather information and accident frequencies

Weather information is obtained from weather stations through the National Climatic Data Center (www.ncdc.noaa.gov). The weather information includes precipitation under normal and extreme conditions such as rain or snow. The roadway accident frequency is obtained from the local transportation agencies (Yazici et al., 2010). The detailed accident records include occurrence time, roadway direction, and position by milepost. In this study, we only collect and analyze the datasets for weekdays.

Step 2: Generate actual link capacity distributions

Incorporated with the weather and accident database, the actual link capacity distributions are calculated by the aforementioned Equations 5-2 and 5-3 using roadway accident data (Yazici et al., 2010) and weather data. The roadway capacity reduction under different weather and accident conditions is based on the information from the literature (Okamoto et al., 2004; Smith et al., 2004; Agarwal et al., 2005).

Step 3: Obtain different samples and calculate the performance cost for each sample

By using the LHS method, 20 different network capacity realizations are sampled. Then, the regional planning model NJRTM-E is repeatedly used to assign the demand matrix with these different network capacity realizations. Finally, we use ASSIST-ME to calculate the total costs based on the network assignment results

Step 4: Detect and rank critical links

We treat the network capacity realizations as inputs, and the total costs calculated by ASSIST-ME as outputs. Then we rank the inputs and outputs by rank transformation technique, respectively, and detect and rank the critical links using various criticality measures.

5.4.3 Capacity Reduction

5.4.3.1 <u>Impact of Accidents</u>

HCM 2000 summarized related studies and identified some guidelines for capacity reduction due to accidents or incidents such as vehicle breakdowns. The proportion of capacity available under accident or incident conditions (number of lanes blocked) was summarized and analyzed, which can be seen in TABLE 5-3.

TABLE 5-3 Freeway Segment Capacity Available Under Incident Conditions

Number of	Shoulder	Shoulder	One Lane	Two Lanes	Three Lanes
2	0.95	0.81	0.35	0.00	N/A
3	0.99	0.83	0.49	0.17	0.00
4	0.99	0.85	0.58	0.25	0.13
5	0.99	0.87	0.65	0.40	0.20
6	0.99	0.89	0.71	0.50	0.26
7	0.99	0.91	0.75	0.57	0.36
8	0.99	0.93	0.78	0.63	0.41

N/A- not applicable
Source: HCM 2000

5.4.3.2 Impact of Extreme Weather

Extreme weather refers to rain, snow, fog, and other adverse weather conditions. Recent research (Okamoto et al., 2004; Smith et al., 2004; Agarwal et al., 2005) emphasized the importance of extreme weather intensity in terms of capacity reduction. The weather reduction factors for this case study can be seen in TABLE 5-4.

TABLE 5-4 Weather Reduction Factors Used for the Case Study

Weather Condition	Rain			Snow			Clear	Others
	Trace (<0.01*)	Light [0.01-0.25]	Heavy (>0.25)	Trace (<0.01)	Light [0.01,0.25]	Heavy (>0.25)		
Capacity Reduction	1-5%	5%-10%	10%-15%	5%-10%	10%-15%	15%-20%	0%	1-5%

* Represented by hourly precipitation

5.4.4 Results and Discussion

Because of the data collection requirements for accident frequencies, it is not practical to obtain such data for short roadway segments that are frequently encountered in the NJTRM-E network model. Moreover, in terms of mathematical formulation and sample-based solution methods, the link conditions are assumed to be independent. However, in reality, the capacity of adjacent links may be correlated with each other. Thus, when calculating risk-related capacity reductions, we attempt to combine several short-distance links in order to incorporate the link capacity correlation observed in reality and also make the network size practical for realistic accident data collection and processing.

The first interesting observation is the characteristics of daily roadway capacity when considering both weather and accident impacts. Among the seven selected routes, in general around 20% of weekday roadway capacities are affected by weather and accident conditions, and 5% of weekday roadway capacities are reduced by more than 15% of the average capacity settings. Most of these severe capacity degradations are caused by accidents. Moreover, we also tried to fit the daily roadway capacities in order to find common probability distributions. However, the daily capacity distributions vary for different roadway sections, and no theoretical distributions can be easily fit.

Note that link criticality is defined as the links that have significant influence on transportation network performance degradation. The criticality measures (RCCs, SRRCs, and PRCCs) are statistical indices for analyzing the relationship between input (link capacity realizations) and output, which is calculated based on the assigned result and ASSIST-ME software tool. The detailed critical link detection and ranking can be seen in TABLE 5-5. The p value is used to test the null hypothesis status that no relationship exists between the involved variables versus the alternative of the probability that a strong linear relationship exists. The lower p value means the test results show that the results are less likely to agree with the null hypothesis. In this study, the facility with the lower p value is the more significant or critical link in the degradable transportation network.

TABLE 5-5 Critical Link Detection and Ranking in Case Study Network

Link no.	Name	RCC		SRRC		PRCC		No. acc Rank*	V/C Rank*
		p value	Rank	p value	Rank	p value	Rank		
4	I-95	0.0000	1	0.0000	1	0.0000	1	3	1
6	NJ-27	0.0031	2	0.0000	2	0.0149	2	2	5
1	I-78	0.0048	3	0.0001	3	0.1435	3	1	2
2	U.S.1&9	0.0059	4	0.0007	4	0.2356	4	5	4
5	I-95	0.0087	5	0.0013	5	0.3347	6	7	3
3	U.S.1&9	0.0132	6	0.0017	6	0.3159	5	4	6
7	NJ-27	0.0347	7	0.0036	7	0.5770	7	6	7

* Rank in descending order according with the values in TABLE 5-2.

Our results demonstrate that the critical links detected by the proposed methodology are correlated with the V/C ratios. TABLE 5-5 shows that most of the links with a high V/C ratio are critical links, such as I-95 and I-78. This is a plausible finding because a high level of usage under normal conditions may imply a potentially significant loss for a degradation scenario. For example, under extreme weather conditions, the interstate highway system may have more significant influence on total performance degradation, compared with regional/local streets. Moreover, statistics (HCM 2000) also indicate that the frequency of accidents/incidents also correlate with link-specific average annual daily traffic (AADT) and V/C ratios.

However, it is also observed that not all the links with a high V/C ratio are consistent with the results presented in TABLE 5-5. An illustrative example is one roadway segment of NJ-27 (Link No. 6). The historical accident rate is high for this link but it has a relatively low V/C ratio. The most likely explanation is that this result may be due to the combination of various causes of possible link degradations. Travelers may switch to paths that include local links under the user equilibrium assumption. Especially for congested traffic conditions, when a number of travelers drive out of a dense urban area, even a partial capacity reduction of a local link (due to an incident or extreme weather) may significantly degrade the roadway network performance.

This is the general criticism by previous studies (Sullivan et al., 2010; Ukkusuri and Yushimito 2009; Scott et al., 2006). The well-known and widely used performance measures such as the V/C ratios are not adequate for planning and maintenance approaches because they are inherently localized and static in nature (Sullivan et al., 2010).

In this study, our main concern is to propose a comprehensive framework that defines a way to incorporate various causes of network capacity degradation into link criticality analysis. The case study is an example employed to show how the proposed framework would work. Although the case study results may be restricted by the regional setting, they still shed some light on the link criticality analysis. Firstly, the proposed framework introduces a novel way to combine different degradation factors into the link criticality analysis via the regional planning model. The results shown in TABLE 5-5 can be considered a comprehensive link criticality evaluation analysis considering the combination of network-wide influence of two degradation factors—namely, extreme weather conditions and incident/accidents. As discussed above, single and localized performance measures are not adequate for transportation planners confronting with a complex transportation system because they may lead to biased results. Second, with the increasing number of sensors being deployed in the real world, this case study is also a demonstration to combine all of the possible empirical data sources together to offer the decision makers more realistic and reliable link criticality results.

5.5 Summary

In this chapter, a novel analytical framework and efficient solution procedure are proposed for the detection and ranking of critical links considering day-to-day degradable transportation network conditions. Sample average approximation (SAA) methodology is used for capturing network capacity uncertainty and solving the formulated stochastic mathematical problem. The difference between the proposed methodology and earlier related work is that rather than using a scenario analysis based on a simple assumption of binary status (fail or not) of link capacity, researchers can use the proposed framework for capturing the day-to-day degradable network conditions for a range of link failure probabilities. Moreover, the proposed framework and methodology define a way to combine all possible empirical data sets together for realistic link criticality evaluation.

To illustrate the proposed methodology, a case study is conducted using a portion of the northern New Jersey network. Total system performance costs based on the assigned volumes of each scenario are calculated using a GIS-based postprocessor that employs New Jersey specific cost functions (Ozbay et al., 2007, 2009; Berechman et al., 2011). These costs are then used to detect and rank the critical links based on various criticality measures described in the paper. The results are found to validate the usefulness of the proposed framework and demonstrate the potential bias if traditional localized and static measures are used. However, it should be noted that the proposed methodology and solution procedure is based on deterministic static traffic assignment, which assumes that drivers have perfect information about the network conditions. It can be more beneficial to investigate the impact of imperfect information by using stochastic user equilibrium assignment. Moreover, the proposed methodology can also be extended to the analysis of time-dependent traffic operations under day-to-day stochastic traffic conditions.

6 CASE STUDY: MODELING EVACUATION TRAFFIC WITH ENDOGENOUS RISKS

Capturing the impact of uncertain events in emergency evacuation planning is an important issue for public officials to avoid unexpected delays and related losses of life and property. However, most of the current studies in evacuation planning only focus on exogenous uncertainties, such as flooding damage in a hurricane, and ignore uncertainties caused by endogenously determined risks, or so-called flow-related risks, such as traffic breakdowns or stop-and-go traffic.

This chapter proposes an analytical framework along with a solution methodology to evaluate the impact of endogenously determined risks in order to develop reliable emergency evacuation plans. We incorporate the probability function of endogenously determined risks in a cell-based macroscopic evacuation model. A network flow algorithm based on the sample average approximation approach is used as part of the solution procedure. Finally, a sample network is used to demonstrate the salient features of the proposed stochastic model and solution procedure.

6.1 Introduction

Evaluating the robustness or so-called resilience of transportation system to accommodate variable and unexpected conditions is essential for human beings' long-term sustainability. The unexpected events, which are the major degradable factors for network supply, can lead to significant congestion and can greatly worsen transportation-oriented services. For example, recently, heavy rains in New Jersey caused road closings due to flooding and led to traffic congestion and accidents (Dinges, 2011). While in Beijing, capacity losses due to routine maintenance caused a one-month 100-kilometer traffic jam (Sainsbury 2010). In fact, failure to consider such unexpected events in the context of pre- and postdisaster transportation planning can negatively affect long-term sustainability of urban areas by making their populations highly vulnerable to the devastating effects of these disasters. During Hurricane Rita, it was observed that "an estimated three million people evacuated the Texas coast, creating colossal 100-mile long traffic jams that left many stranded and out of fuel; inefficient use of road capacity and the effects of ill-planned evacuation resulted in disorganized movement of people" (Litman 2006).

This chapter attempts to incorporate and evaluate the endogenously determined risks, especially breakdowns in the context of emergency evacuation planning. Several features distinguish this study from the previous evacuation studies (Yazici and Ozbay 2008, 2010; Ng and Waller 2010). First, this chapter proposes a comprehensive analytical framework that incorporates the endogenously determined risks into the emergency evacuation planning process. In order to capture the endogenously determined risks, the roadway capacities are modeled as variables that are dynamically readjusted over time based on the assigned flows. Second, the characteristics of flow-related risks, including probability, duration, and capacity degradation levels, are modeled through a computationally feasible cell-based macroscopic dynamic traffic assignment model. Note that our model is not based on a mesoscopic / microscopic simulation model such as the one proposed in Dong and Mahmassani (2009). This is important because our use of a macroscopic model makes it possible to solve it using well-known network flow algorithms and also theoretically guarantee convergence to a system optimal solution as will be briefly discussed later in this study. Third, since roadway capacities are dynamically updated, the common linear programming solvers cannot be used for solving the proposed model. To remedy this problem, a network flow algorithm is used in this chapter. The advantage of the network flow algorithm is that through the use of successive shortest-path maximum-flow algorithms, it is feasible to trace the origin-destination paths and update the roadway properties dynamically.

6.2 Modeling Framework

This chapter attempts to construct a planning-oriented tool that can assist researchers or policy makers to better evaluate the evacuation process due to natural disasters by incorporating more realistic traffic operation conditions. The proposed framework is planning oriented and does not attempt to address real-time decision-making issues. The whole evacuation process is divided into *N* stages. Basically, we claim that evacuation demand loading at a certain evacuation stage will potentially cause transportation network degradation in the next several stages. The term of network degradation refers to the concept of capacity reduction of a certain roadway or link caused by flow-related risks. In general, the transportation network condition is considered a dynamic degradation process, and its current condition is dependent on the demand loading in the previous stages. The proposed modeling framework that depicts this idea is shown in FIGURE 6-1.

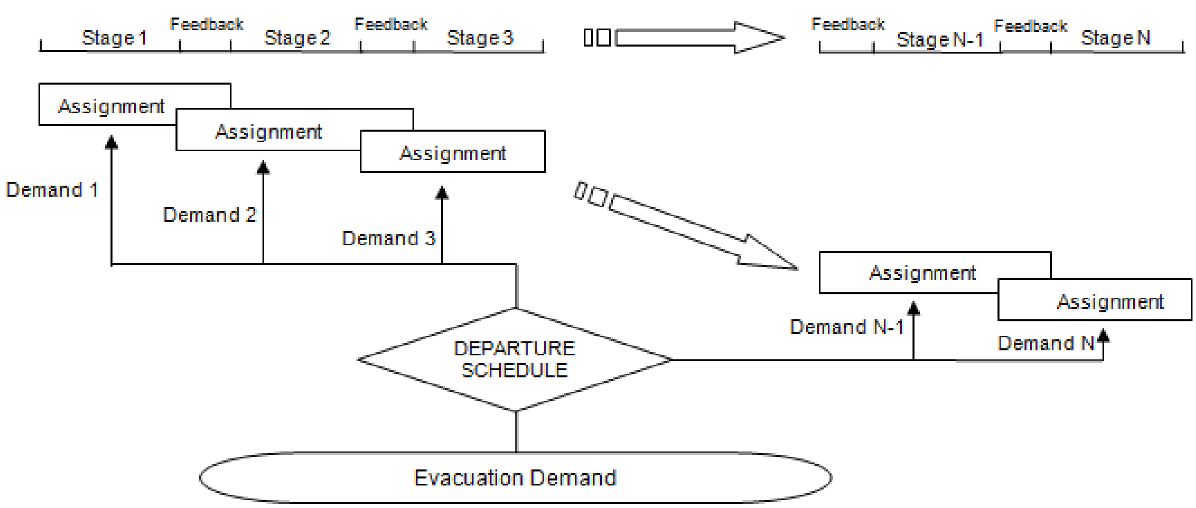


FIGURE 6-1 Framework for Emergency Evacuation Considering Flow-Related Risks.

The first set of questions related to the above framework is about the definition of a stage, total number of stages required, and spatial distribution of risk severity. These questions can only be answered on a case-by-case basis according to the type and time of the occurrence of an emergency, which warrants an evacuation under prevailing background traffic and network conditions. On the one hand, the optimization of real operations in the presence of an emergency situation needs sufficient online and off-line data, which may restrict the definition of a stage. On the other hand, when considering flow-related risks, the feedback process may be too complex to model and thus optimize the total evacuation process.

The next question is how to model the feedback process to consider flow-related risks. The most straightforward way is at the end of each stage (a) to correlate current link volumes with a historical breakdown database and determine the probability that breakdown would occur given the prevailing links flows, (b) to simulate potential capacity reductions as a function of different breakdown occurrence probabilities, and (c) to analyze the results by employing different performance measures (e.g,. average evacuation clearance time and its variance). Using a reliable breakdown database coupled with corresponding link flow data, we can incorporate the idea of a flow-dependent link capacity concept into the formulation of the evacuation problem by means of a multistage stochastic programming model.

The final question is the evacuees' departure schedule. The detailed departure information is usually obtained by surveying people for different threat scenarios. Scenarios are usually described in terms of basic information about the nature of the disaster, mainly conditions that might be experienced immediately after a disaster. Overall, the survey makes it possible to examine the evacuation decision changes for different types of threats and with respect to the proximity of the possible evacuee to the hypothetical disaster location, along with the overall evacuation destinations and available mode choices. An example of this kind of survey can be found in Carnegie and Deka (2010).

6.3 Analytical Evacuation Models

Analytical evacuation models can be generally categorized as macroscopic and microscopic. Macroscopic models usually formulate the evacuation process as an optimization problem without considering the differences between individual evacuees' behavior. Instead, evacuees are separated as several homogeneous groups with common behavioral characteristics. Thus, macroscopic models are mainly used to estimate lower bounds of evacuation time for regional plans, such as hurricanes, forest fires, and nuclear power plant failures. Microscopic models pay more attention to capturing evacuees' individual behavior and the interactions among them. The models are used for pedestrian evacuation in a small urban area (Chio et al., 1988). In this study, we mainly focus on a macroscopic evacuation model for relatively large regions.

Since computational complexity and time are essential issues dealing with large networks in the context of evacuation planning, advances in macroscopic models are usually related to the discrete time dynamic network flow problem, which is a discrete time expansion of static network flow problem. The general model is formulated as a linear programming model with the constraints of flow propagation and link properties. The objective function is formulated in a primal-dual way: either to minimize the total cost during the time horizon given the total number of evacuees, such as a dynamic minimum cost flow (DMCF) problem, or maximize the dynamic flows reaching the sink in the time horizon, see the problem of dynamic maximum flow (DMF, Ford and Fulkerson, 1958) problem. In other words, the DMCF problem aims to assign the flow dynamically in order to minimize the total cost throughout the specified time horizon. Thus DMF problem can be interpreted as the evacuation process of transferring as many evacuees as possible within the given time horizon. An extension of the DMF is universal maximum flow problem (UMF, Gale 1959) and quickest flow problem (QF, Burkard 1993). The UMF is showed to determine DMF not only in a given time horizon but also at each discrete time step. QF was formulated for finding the minimum evacuation clearance time given the evacuation demand.

Jarvis and Ratliff (1982) first proved that among the DMCF, UMF, and QF problem, the solution of either DMCF or UMF was also the solution of the other two problems. In other words, DMCF is shown to be equivalent to the UMF problem. This important theorem can be seen below. The detailed proof can be found in Jarvis and Ratliff (1982). The proof of equivalence of DMCF and UMF problems can also be found in Choi et al. (1988).

THEOREM (Javis and Ratliff, 1982). Consider a dynamic network flow problem with arcs *A*, source *S*, and sink *T*. Suppose we distinguish the nodes $t_1, \ldots, t_n$ leading to the sink, with the flow F_j on arc (t_j, T) being the flow into *T* in period *j*.

Consider the three objectives (a), (b), and (c), below. Any feasible flow of *K* units from *S* to *T* that satisfies either condition (a) or condition (b) also satisfies the other two.

(a) Maximize $\sum_{j=1}^{p} F_j$ for $p = 1, 2, \ldots, n$ (i.e., maximize the output for the first *p* periods for all values of *p*).

(b) Minimize $\sum_{j=1}^{n} c_j F_j$ where $c_1 < c_2 < \cdots < c_n$ (i.e., minimize the weighted sum of flows where the weights are increasing with time).

(c) Minimize p such that $F_{p+k} = 0$ for $k = 1, 2, \ldots, n - p$ (i.e., minimize the number of periods required to send a flow of *K* from *S* to T).

For the state-of-practice macroscopic models in evacuation planning, the Cell Transmission Model–based System Optimal Dynamic Traffic Assignment (CTM-SO-DTA, Ziliaskopoulos 2000), which is shown to be equivalent to the DMCF problem with constraints of practical traffic characteristics, is widely used as a basic model for various applications, such as a robust evacuation schedule (Liu et al., 2006; Chiu et al., 2007), and uncertainty analysis in either network supply (Yazici and Ozbay 2008) or evacuee demand (Yao et al., 2009), or both supply and demand sides (Yazici and Ozbay 2010; Ng and Waller 2010). Moreover, recently, Zheng and Chiu (2011) also proved that the CTM-SO-DTA was equivalent to the UMF problem, even in a network with time-varying parameters. Their proof shed light on the solution procedure of the proposed model. A detailed explanation of the model and the solution process can be found in the next section.

6.4 Modeling Endogenous Risks via Cell Transmission Model (CTM)

6.4.1 Cell Transmission Model

CTM, proposed by Daganzo (1994, 1995), is widely used as a fundamental tool to capture and analyze realistic traffic phenomena and related problems. The general modeling approach is given as follows: given the time period and transportation network, the CTM first separates the continuous time into small time steps and divides each link in the network into subsegments, or cells. Depending on merge/diverge topological structure, the cells are generally grouped into three categories: the ordinary cell with only one upstream cell and one downstream cell, the merging cell with one upstream cell and more than one downstream cell, and the diverging cell with more than one upstream cell and one downstream cell. The demonstration of cell transmission and classification of cells can be seen in FIGURE 6-2.

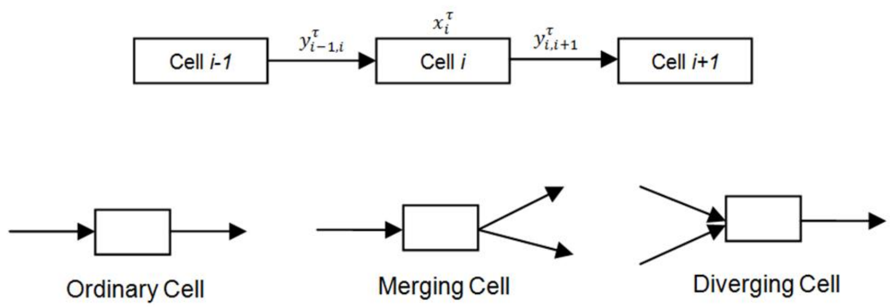


FIGURE 6-2 Example of Cell Transmission and Classification of Cells

The length of each cell is equal to the maximum distance that vehicles can travel in one time step. In other words, the vehicles can at most move one cell ahead in each time step. The vehicles moving from a certain cell to the downstream cell is restricted by two rules: flow conservation and the flow-density relationship. Flow conservation refers to the requirement that vehicles entering a cell cannot vanish before reaching their destination (see Constraint 6-1 as an example of an ordinary cell i). The occupancy of cell i at time step $\tau + 1$ ($x_i^{\tau+1}$) is equal to the occupancy of cell i at time step τ, plus the number of vehicles $y_{i-1,i}^{\tau}$ from upstream cell and minus the number of vehicles $y_{i,i+1}^{\tau}$ to downstream cell at time step τ. The different representations of merging and diverging cells can be seen later in the proposed model description.

$$x_i^{\tau+1} = x_i^{\tau} + y_{i-1,i}^{\tau} - y_{i,i+1}^{\tau} \tag{6-1}$$

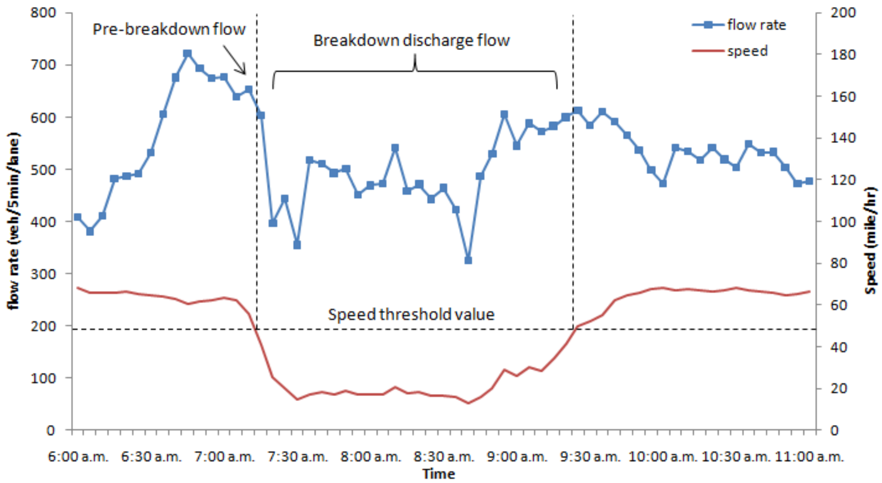
The flow-density relationship states that the number of vehicles that traverse from ordinary cell i to downstream cell $i + 1$ at time step τ must satisfy Constraint 6-2. x_i^{τ} is the number of vehicles in cell i at time step τ. Q_i^{τ} and Q_{i+1}^{τ} are the maximum flow rate at time step τ that can departure/arrive of cell i and $i + 1$, respectively. N_{i+1}^{τ} is the maximum flow allowed to be accommodated in cell $i+1$ at time step τ . $\delta(N_{i+1}{}^{\tau} - x_{i+1}{}^{\tau})$ δ $(N^{\tau}_{i+1} - x^{\tau}_{i+1})$ is the remaining occupancy at the downstream cell, and δ is the ratio of the backward wave speed to the forward wave speed. The different representations of merging and diverging cells can be seen later in the proposed model description.

$$y_{i,i+1}{}^{\tau} = \min\{x_i{}^{\tau}, Q_i{}^{\tau}, Q_{i+1}{}^{\tau}, \delta(N_{i+1}{}^{\tau} - x_{i+1}{}^{\tau})\} \tag{6-2}$$

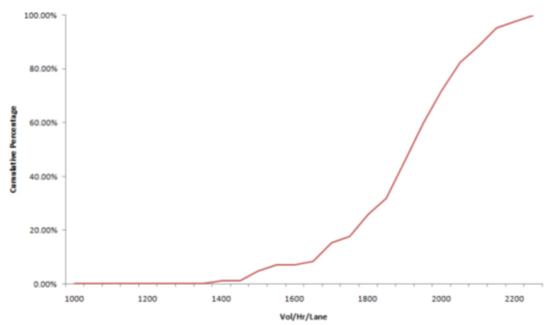
6.4.2 Modeling Endogenous Risks within the Context of CTM

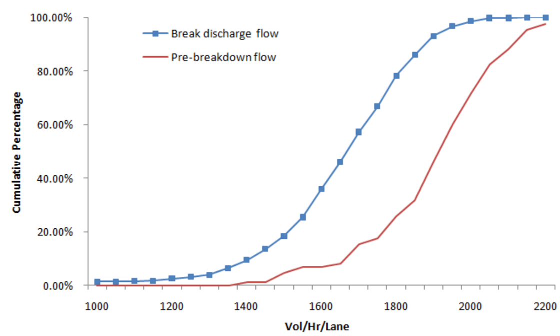
Empirical observations (Persaud et al., 1998; Lorenz and Elefteriadou, 2001) of freeway traffic show that the congestion usually starts from a sudden vehicle speed drop. Traffic engineers call this sudden speed drop the flow breakdown. An example of breakdown can be seen in FIGURE 6-3(a). Usually traffic breakdown is defined as when the average speed of traffic drops below a certain threshold. In FIGURE 6-3(a), the breakdown starts at 6:30 and ends at around 8:45.

Traffic breakdowns cause congestion and change the definition of highway capacity. The traditional definition of highway capacity in HCM (2000) is the maximum flow rate that can reasonably be expected to traverse a facility under prevailing roadway, traffic, and control conditions. However, it is known that traffic breakdown is a stochastic phenomenon that can happen even when the traffic flow is below the capacity. With emerging data sources available, most studies prefer to recognize highway capacity as a stochastic value but not a constant one. Lorenz and Elefteriadou (2001) proposed a new definition of the traffic capacity by introducing probabilistic concepts. “The capacity is understood as the traffic volume below which traffic still flows and above which the flow breaks down into stop-and-go.”



(a) Flow rate and speed time series during a breakdown





(b) Estimated capacity distribution (c) Capacity drop

FIGURE 6-3 An Example of Traffic Breakdown, Estimated Capacity Distribution, and Capacity Drop (PeMS, 2013)

In order to obtain the distribution of freeway capacity, Brilon et al. (2005) proposed a methodology that was based on statistical life time analysis by using the Kaplan-Meier estimator. Various plausible functions such as Weibull, Normal, and Gamma distributions were calibrated to match the empirical observations. The results showed that the Weibull distribution fit better with the empirical data. An example of estimated capacity distribution can be seen in FIGURE 6-3(b). Ozguven and Ozbay (2008) used the above methodology and investigated the spatial and temporal difference of the freeway section on the capacity distribution. The results indicated that the curves obtained by the Weibull distribution were smoother than the other estimator. The detailed Weibull distribution can be seen below.

$$F(q) = 1 - e^{-(\frac{q}{\sigma})^{s}} \tag{6-3}$$

Where

$F(\cdot)$ = probability distribution function

q = pre-breakdown flow rate

σ = scale parameter

s = shape parameter

Besides the probability of breakdown, empirical studies also found that roadway capacities were different between congested flows during breakdown and uncongested flows. The discharge flow rates at bottlenecks during breakdowns are reduced. These flow reductions, also known as capacity drops, are typically measured by comparing the queue discharge flow rate to the maximum pre-queue discharge flow rate. A summary of capacity drops associated with different bottlenecks are summarized by Chamberlayne et al. (2012) in TABLE 6-1.

TABLE 6-1 Summary of Empirical Capacity Drops (Chamberlayne et al., 2012)

Reference	Bottlenecks example	Location	Capacity drop
Hall and Agyemang-Duah (1991)	On-ramp merge	QEW—Mississauga	5%–6%
Banks (1991)	On-ramp merge	I-8—San Diego (site 1)	10.5% (left lane) 3% (across all lanes)
Cassidy and Bertini (1999)	On-ramp merge	QEW—Mississauga	8%–9%
Cassidy and Rudjanakanoknad (2005)	On-ramp merge	I-805—San Diego	10%
Chung et al. (2007)			
Chung et al. (2007)	Lane drop	SR-24—San Francisco	5%–8%
Persaud et al. (1998)	On-ramp merge	Highway 401 & Gardiner Expwy—Toronto	11%–17%
Bertini and Leal (2005)	Lane drop	M4 motorway—London I-494—Minneapolis	10% 12%

The breakdown duration is another concern. Kim et al. (2010) recently examined duration of breakdown under different weather conditions. Significant factors that affect breakdown duration were identified and calibrated. However, these conclusions still need more validation considering variability in breakdown behavior. Moreover, modeling breakdown duration in evacuation is different with daily traffic. Usually breakdown patterns are similar in different workdays. For example, the daily breakdown may happen and end at a similar time during the morning or evening peak periods. Thus, it makes sense to model such patterns of breakdown duration in daily traffic conditions. But during evacuation, the traffic patterns may be similar to those during a peak period but can possibly last one day or even more. The duration of breakdown in daily traffic cannot be used in evacuation modeling.

In this study, we reformulate the CTM in order to capture the breakdowns. Because the breakdowns usually happen at freeway bottlenecks, especially at on-ramps or interchanges, in this study, we only consider the capacities of merging cells as stochastic parameters. The cell capacity at time step τ is assumed to follow a conditional probability function based on the flow rate at the previous time step $\tau-1$. In other words, the cell capacity is dynamically updated at each time step based on the flow.

FIGURE 6-4 shows the flowchart for modeling breakdown at time step τ. For each merging cell, first we check if the flow rate y_{ij}^{τ} is greater than the threshold flow rate $\overline{y_{ij}}$ (please see FIGURE 6-3[b] for an example of the threshold flow rate). If $y_{ij}^{\tau} < \overline{y_{ij}}$ then no breakdown happens at time step τ, and cell capacity Q_i^{τ} is equal to default capacity Q_i^{0}; otherwise the breakdown happens at time step τ. If a breakdown happens, go back to check the cell status at the previous time step. If a breakdown happened at time step $\tau - 1$, we assume the breakdown continues at time step τ, and cell capacity Q_i^{τ} is equal to $Q_i^{\tau-1}$; otherwise, if no breakdown happened at time step $\tau-1$, then a random number p_i^{τ} is generated and compare with the breakdown probability $p_i(y_{ij}^{\tau})$ at cell i. If $p_i^{\tau} > p_i(y_{ij}^{\tau})$, then a new breakdown happens at time step τ, and capacity is $Q_i^{\tau} = (1-\alpha)\cdot Q_i^{0}$, where α is the parameter of capacity drop. When applied in real situations, the specific formulation and calibration of probability function p_i may vary according to the availability of databases of breakdowns and link flows.

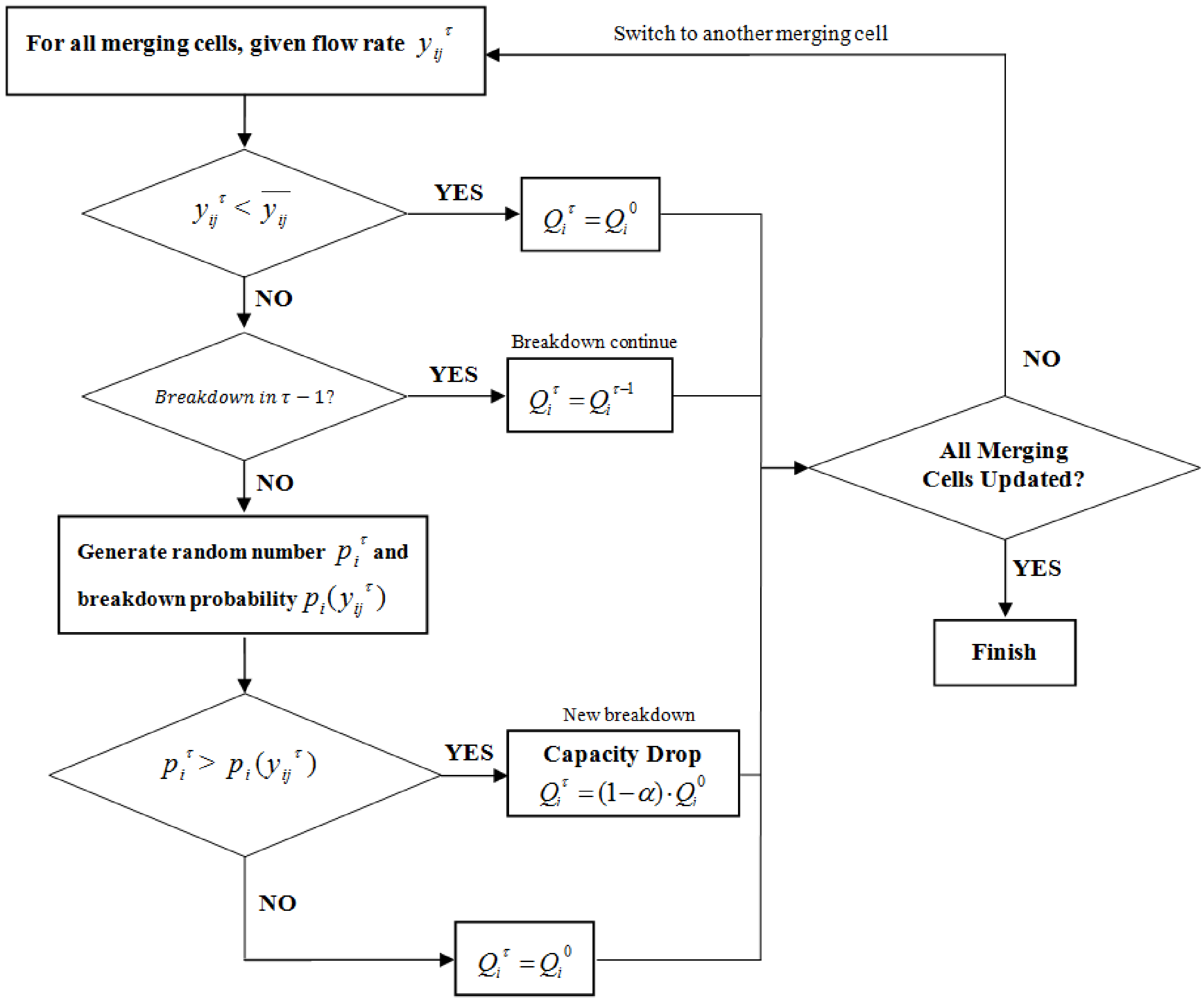


FIGURE 6-4 Flowchart for Modeling Breakdowns by CTM

6.5 The Proposed Model and Solution Procedure

6.5.1 The Proposed Cell-Based Stochastic DTA Model

In order to capture the endogenous risks, we modify original CTM-SO-DTA model (Ziliaskopoulos 2000), introducing the cell capacity Q_i^{τ} as a stochastic parameter and the corresponding constraint (6-11) and objective function (6-4). Since the constraint (6-11) is a probability function, when solving the model, the solution may vary for each realization of the probability function. The expectation of total system users' evacuation time is used as the objective function. Constraint 6-5 is used to ensure the flow conservation considering all cell types. Constraint 6-6 is the cell mass balance for the source cells. Constraints 6-7–6-10 express the flow-density relationships for different cell types in CTM. The rule of the flow-density relationship in CTM is assumed to be a triangular shape, which can be seen in Dangazo (1994). Constraints 6-12 and 6-13 are the variables' initial value setting and the nonnegative condition.

Symbol	Description
d_i^{τ}	Time-dependent demand at cell *i* at time interval τ τ .
C	Set of cells: ordinary cells (C_O), diverging cells (C_D), merging cells (C_M), source cell (C_R) and sink cells (C_S).
E	Set of connectors: ordinary cell connectors (E_O), diverging cell connectors (E_D), merging cells connectors (E_M), source cell connectors (E_R), and sink cell connectors (E_S).
$\Gamma(i)$	Set of successor cells to cell *i*.
$\Gamma^{-1}(i)$	Set of predecessor cells to cell *i*.
τ	Discrete time interval, $\tau = 0...T$ $\mathrm{t} = 0..\mathrm{t_m}$.
T	Time horizon.
N_i^{τ}	Jam density of cell *i* at time interval τ .
Q_i^{τ}	In and out saturation flow of cell *i* during time interval τ .
x_i^{τ}	Cell occupancy is the number of vehicles in cell *i* at time interval τ .

y_{ij}^{τ} Flow is the number of vehicles moving from cell *i* to cell *j* at time interval τ .

δ_j^{τ} The *v/w* ratio for each cell at each time interval τ , *v* is link free flow speed, and *w* is backward propagation speed.

$$Min: E(\sum_{t\in T}\sum_{i\in C\backslash C_S} x_i^{\,t}) \tag{6-4}$$

$s.t.$

$$x_i^{\tau} - x_i^{\tau-1} - \sum_{k\in\Gamma^{-1}(i)} y_{ki}^{\tau-1} + \sum_{k\in\Gamma(i)} y_{ij}^{\tau-1} = 0, \quad \forall i\in C\,|\,\{C_R, C_S\}, \forall\tau\in T \tag{6-5}$$

$$x_i^{\tau} - x_i^{\tau-1} + y_{ij}^{\tau-1} = d_i^{\tau}, \ \forall j\in\Gamma(i), \forall i\in C_R, \forall\tau\in T \tag{6-6}$$

$$\sum_{j\in\Gamma(i)} y_{ij}^{\tau} - x_i^{\tau} \le 0, \ \forall i\in C\,|\,\{C_R\}, \quad \forall\tau\in T \tag{6-7}$$

$$\sum_{j\in\Gamma(i)} y_{ij}^{\tau} \le Q_i^{\tau}, \ \forall j\in C\,|\,\{C_R, C_S\}, \forall\tau\in T \tag{6-8}$$

$$\sum_{i\in\Gamma^{-1}(j)} y_{ij}^{\tau} \le Q_j^{\tau}, \quad \forall j\in C\,|\,\{C_R, C_S\}, \forall\tau\in T \tag{6-9}$$

$$\sum_{i\in\Gamma^{-1}(j)} y_{ij}^{\,t} + \delta_j^{\,t} x_j^{\,t} \le \delta_j^{\,t} N_j^{\,t}, \ \forall j\in C\,|\,\{C_R, C_S\}, \forall\tau\in T \tag{6-10}$$

$$Q_i^{\tau} = f(Q_i^{\tau-1}\,|\,y_{ij}^{\tau-1}), \ \forall i\in C_M, \forall\tau\in T \tag{6-11}$$

$$x_i^{0} = 0, y_{ij}^{0} = 0, \forall i\in C, \forall(i,j)\in E \tag{6-12}$$

$$x_i^{\tau} \ge 0, y_{ij}^{\tau} \ge 0, \forall i\in C, \forall(i,j)\in E, \forall\tau\in T \tag{6-13}$$

When considering endogenous risks, the traffic assignment process is not trivial. Because of endogenous risks, a suboptimal evacuation demand loading for a certain stage may potentially cause transportation network disruptions and delays during the next several stages. Thus, for a certain departure schedule, although the predicted or expected evacuation clearance time may be acceptable, there may still be a potential high risk of capacity losses. Then the assignment strategies or so-called departure schedule may possibly affect the optimal solutions.

In the evacuation situations, especially no-notice evacuation, it is not practical to determine an optimal departure schedule. The evacuees' response behavior vis-à-vis an evacuation order may vary (e.g., as a rapid or slow response). For the planners, the main concern is the worst-case scenario: assuming all the evacuees start evacuation when an emergency situation first emerges, what is the estimated evacuation time considering realistic roadway network conditions? This is the primary objective in this study. The model is formulated not for determining the "optimal" evacuation plans but to evaluate the evacuation process for realistic conditions. The results and analysis are based on probability measures instead of point estimates to evaluate the robustness and the performance of a road network under emergency conditions.

Note that because of the "additional" constraint of endogenous risks, the proposed model cannot be solved by commercial LP solvers. In order to solve the proposed stochastic DTA model, a heuristic solution procedure via a sample average approximation is proposed in the next section.

6.5.2 A Heuristic Solution Procedure

Network flow algorithms offer feasible solution approaches to solving the proposed model. According to equivalence of DMCF and UMF problems, the DMCF problem can be solved as the UMF problem. Since the UMF problem can determine maximum arrival flow for each discrete time step, when solving the UMF problem, it is only needed to successively augment maximum flow along the shortest path on the time-expanded network. Thus, the common idea of these algorithms is to reformulate the problem via a time-expanded network structure with the model constraint set and solve the model by augmenting maximum flow successively using the shortest path algorithm over the time-expanded network (Liu et al., 2007, Zheng and Chiu, 2011).

Specifically, the proposed model can be solved by augmenting maximum flow along the shortest path on the residual time-expanded network at each time step τ, until there is no additional shortest path available, which indicates that at the time step τ the flow achieves an optimal solution. Then, the time-expanded network is extended from τ to $\tau + 1$ and the above procedure is repeated until all the demands are satisfied or the time horizon T is reached. The work by Liu et al. (2007) and Zheng and Chiu (2011) indicate that network flow algorithms have better computational efficiency compared with common LP solvers. Moreover, the solution process is feasible for tracing successive shortest paths. This makes the proposed problem solvable in a finite time. In the feedback process between two consecutive time intervals, the link capacity can be updated according to the current time-staged degradation status, which is dependent on the probability function of the previously assigned flow.

For solving the model with the expected value as the objective function, a common approach is to replace the probability function $f(\cdot)$ with a finite supported measure. The main idea of SAA is based on Monte Carlo simulation. That is, suppose $f(\cdot)$ has a finite number of possible realizations, $(\xi_1, \xi_2, \ldots, \xi_m)$ with respective probabilities $p_m \in (0,1), m = 1,2,\ldots, M$. For such problems, the expected value function in (4) can be written as the following finite sum:

$$Min \qquad \sum_{m=1}^{M} p_m (\sum_{t\in T} \sum_{i\in C\backslash C_S} x_i^{\ t}) \tag{6-14}$$

In this study, each of the realizations has the same probability. Clearly if we were using different scenarios, different probabilities would have been needed for each scenario according to the likelihood of occurrence of each scenario. However, in our model we introduced a flow-related link capacity function, and the cell capacity may be reduced to a certain level according to this probability function for each time step in the assignment. Thus, the results may vary for each separate assignment. That is the reason we use SAA to optimize the average assignment results. It is important to state that the idea of SAA is very similar to Monte Carlo simulation where different simulations have identical probability. Thus, Equation 6-15 can be written as follows:

$$Min \qquad M^{-1} (\sum_{t\in T} \sum_{i\in C\backslash C_S} x_i^{\ t}) \tag{6-15}$$

The function shown in 6-14 and 6-15 is an unbiased estimator of the expected value of the objective function shown in Equation 6-4, and by the Law of Large Numbers, 6-14 and 6-15 converges to 6-4 when $M \to \propto$. This suggests that an SAA problem with a modest sample size will provide a fairly good approximation of the original problem. Moreover, in the SAA procedure, each realization can often be considered independently from other realizations. This makes such algorithms well suited for implementation on parallel computing platforms, where different processors can execute independent realization in parallel. Interested readers are referred to Helton et al. (2006) for more detailed discussion.

In the proposed mathematical formulation, for a certain departure schedule, the stochastic constraint in 6-11 represents the possible link capacity reduction caused by the demand loaded during the previous time step. We can employ the above procedure and calculate the required objective function by repeating the network flow algorithm described in the previous section with the proper number of samples. The details of the SAA procedure can be seen in FIGURE 6-5.

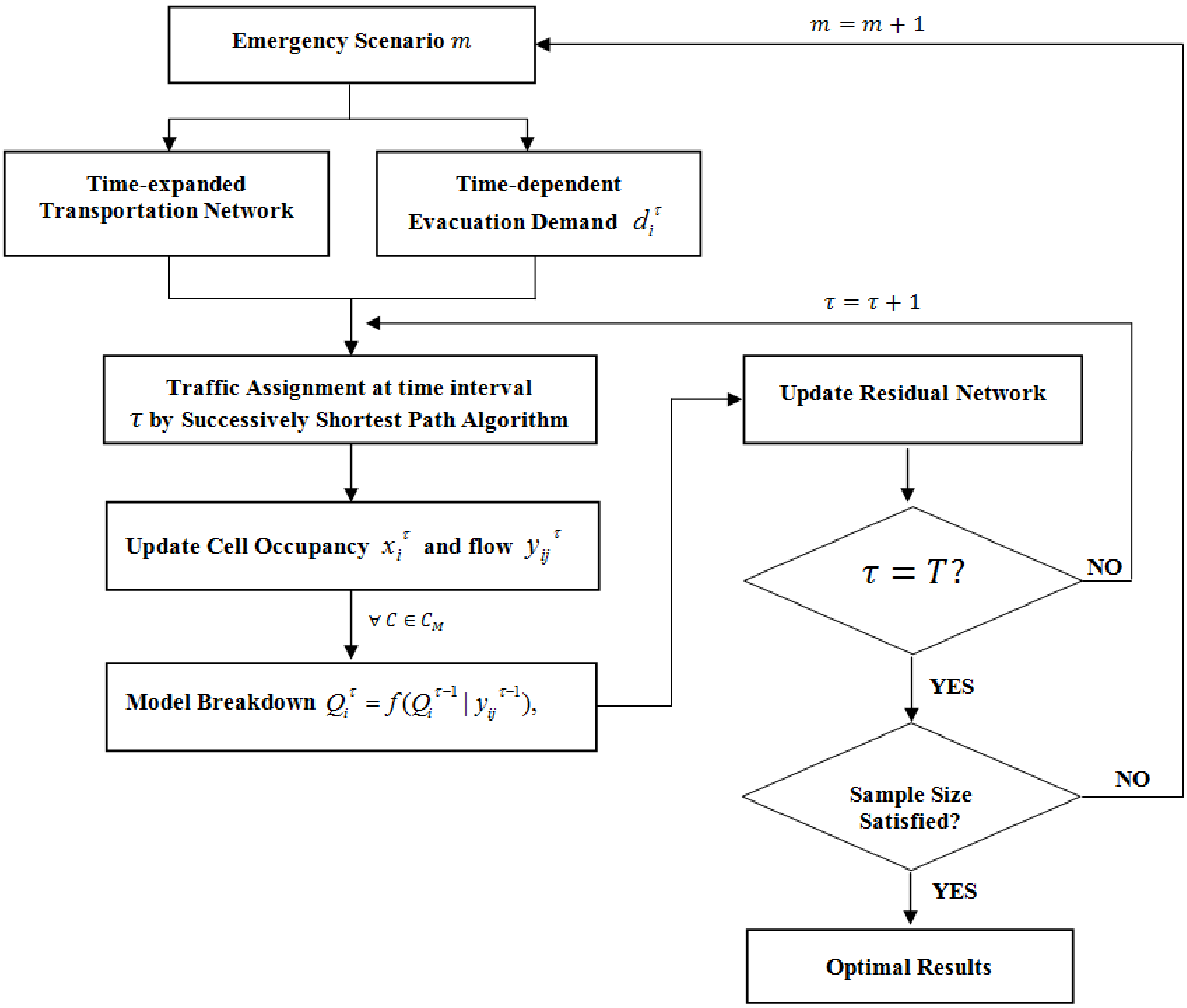


FIGURE 6-5 Flowchart of the Proposed Solution Procedure

6.6 Numerical Example

6.6.1 Study Network and Scenarios

We present a numerical example to demonstrate the proposed methodology and solution algorithm. The transportation network given in Ziliaskopoulos (2000) is used as the test network. The cell representation of this simple six-node, seven-link network can be seen in FIGURE 6-6. The cell properties are shown in TABLE 6-2.

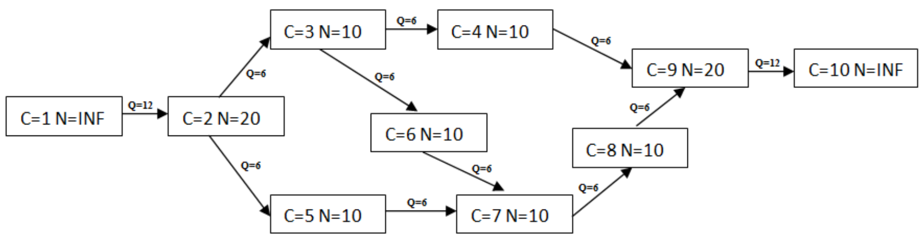


FIGURE 6-6 Cell Representation of the Test Network (Ziliaskopoulos, 2000)

TABLE 6-2 Cell Properties in the Test Network (Ziliaskopoulos, 2000)

Cell	2	3	4	5	6	7	8	9
$N_i^{t,n,s}$	20	10	10	10	10	10	10	20
$Q_i^{t,0,s}$	12	6	6	6	6	6	6	12
$x_i^{0,0,s}$	0	0	0	0	0	0	0	0
$\delta_j^{0,0,s}$	1	1	1	1	1	1	1	1

We assume that a no-notice emergency occurs and all the evacuees have to evacuate from the emergency area (cell 1) to a safe area (cell 10). The total evacuation demand is assumed to be 100 units. The transportation agency's priority is to determine the reliable evacuation clearance time and possible departure schedule, minimizing potential risks. Without loss of generality, we assume that total evacuation demand is released at the beginning of evacuation process (time step 0).

In this numerical example, flow-related breakdown is considered in order to verify the proposed framework/model and solution procedure. Because breakdowns usually happen at freeway bottlenecks, especially on-ramp merging sections. Thus, in this numerical example, breakdowns were only considered in the merging cells 7 and 9. The probability function of breakdown is assumed by following a Weibull distribution. The capacity drop during breakdown is assumed to be 20%–30% of default capacity setting.

6.6.2 Analysis of Results

The results can be seen in TABLE 6-3 and TABLE 6-4. TABLE 6-3 is the deterministic model result without considering flow-related risks (full capacity case), while TABLE 6-4 shows the result of the proposed model solved by using the proposed SAA procedure. Compared with theoretical spatial-temporal patterns of evacuees shown in TABLE 6-3, the results of the proposed model appear to be more realistic in terms of traffic congestion patterns during an evacuation process. When considering flow-related risks, the total evacuation clearance time increased from 13 to 15 time steps. When the evacuees are continuously loaded onto the network, the occupancy increases and reaches its maximum value at time step 8, and then congestion is reduced due to the decrease in evacuation demand. Moreover, the flow-related risks cause congestion due to spill back, as seen in cell 2. Since cell 2 is the first roadway segment connecting the rest of the network with the evacuation area, it is reasonable to have most of the evacuees holding or blocking around the place where the emergency evacuation starts.

TABLE 6-3 Evacuation Flows without Considering Flow-Related Risks

Cell	Time													
	0	1	2	3	4	5	6	7	8	9	10	11	12	13
1	100	88	76	64	52	40	28	16	4	0	0	0	0	0
2	0	12	12	12	12	12	12	12	12	4	0	0	0	0
3	0	0	6	6	6	6	6	6	6	6	4	0	0	0
4	0	0	0	6	6	6	6	6	6	6	6	4	0	0
5	0	0	6	6	6	6	6	6	6	6	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	6	6	6	6	6	6	6	6	0	0	0
8	0	0	0	0	6	6	6	6	6	6	6	6	0	0
9	0	0	0	0	6	12	12	12	12	12	12	12	10	0
10	0	0	0	0	0	6	12	12	12	12	12	12	12	10

TABLE 6-4 Evacuation Flows when Considering Flow-Related Risks

Cell	Time																
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	100.0	88.0	76.0	64.0	52.0	40.0	28.0	16.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	12.0	12.0	12.5	13.4	13.7	13.9	14.5	14.6	6.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	4.4	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	6.0	6.0	5.9	5.4	5.5	5.9	5.9	5.8	4.4	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	6.0	5.5	5.1	5.7	5.8	5.4	5.8	6.4	3.9	0.2	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.1	0.6	0.5	0.1	0.1	0.2	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	6.0	5.5	5.1	5.8	7.4	8.5	9.5	9.8	9.2	5.0	0.7	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	6.0	5.5	5.1	4.8	4.7	4.5	4.5	4.5	4.5	4.3	0.7	0.0	0.0
9	0.0	0.0	0.0	0.0	6.0	12.0	11.4	11.9	12.9	14.4	15.8	17.0	16.9	12.4	7.7	0.7	0.0
10	0.0	0.0	0.0	0.0	0.0	6.0	12.0	10.0	9.3	9.2	9.0	9.0	9.0	9.0	9.0	7.7	0.7

In addition to the estimation of average evacuation times, deviation of evacuation times for the mean value or the probability distribution are among other ways for evaluating the feasibility of evacuation routes or plans. For instance, from distributional properties, the percentile of the evacuated population vs. time graphs can be obtained. This kind of distributional approach provides better insights into the problem such as by estimating the number of people in danger after the passage of a certain amount of time from the issuance of the evacuation order.

The results analyzed from a probabilistic point of view confirm the usefulness of the proposed model. In FIGURE 6-7, we can visually observe the significant impact of flow-related risks. Compared with the best case, by the time all evacuees arrive in the safe area, more than 20% of evacuees still remain in the congested network in the case of the worst-case scenario. Moreover, the evacuees' arrival patterns are not only captured in terms of an average value but also using the corresponding value of the standard variance. The value of the standard variance can be interpreted as the confidence level of estimated evacuation times at a certain time step. In the early stages, we are confident with the evacuation time estimation. With the increasing number of evacuees loaded onto the network, the standard deviation sharply increases when breakdown happens. As the evacuation process continues to evolve, the values of standard deviation drop and keep stable because the network is congested even though the travel is slow but more predictable with a lower standard deviation. The high deviation in the end is caused by the possible release of the breakdown.

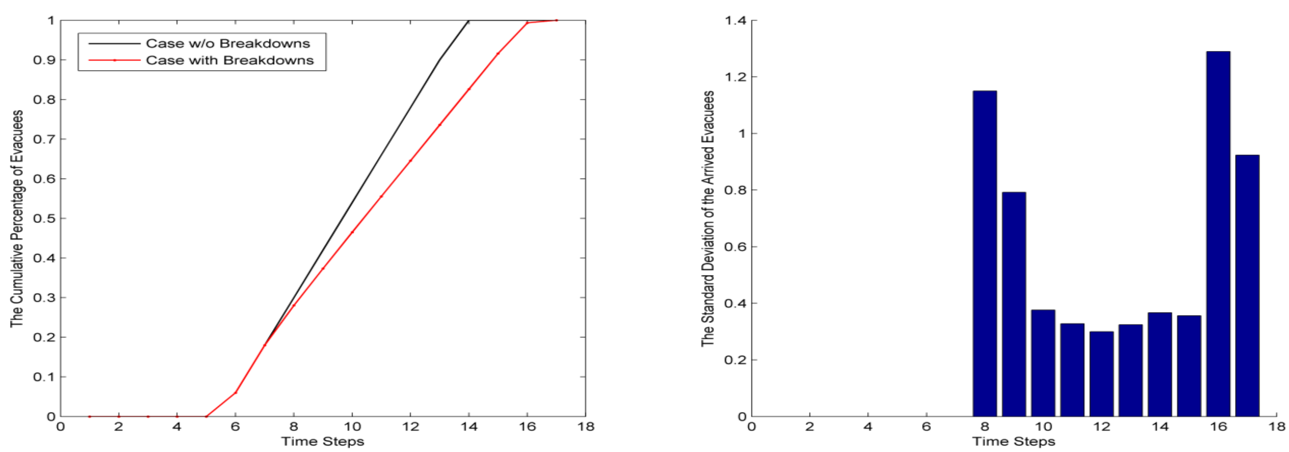


FIGURE 6-7 Evacuation Arrival Patterns: Cumulative Percentage and Standard Deviation

As we have discussed above, partial capacity reductions along the evacuation routes may cause a chain reaction (backward shock wave) and significantly delay the evacuation process. During Hurricane Rita, mass evacuation demand caused traffic jams that left many motorists stranded and out of fuel. Then a vicious circle happened with more vehicles stuck in congestion running out of fuel and reducing roadway capacities even more, causing queues as long as 100 miles (Litman, 2006). Alternative route information for diverting traffic is important when this kind of congestion as a result of flow-related capacity reductions occurs.

Since the successive origin-destination paths generated by the proposed solution procedure are traceable, another interesting observation is the evacuees' possible rerouting behavior due to the congestion caused by flow-related risks. In the numerical example, without considering endogenous risks, because of the specific capacity constraint of cell 2, the evacuees only choose the other two paths—namely, $1 \to 2 \to 3 \to 4 \to 9 \to 10$ and $1 \to 2 \to 5 \to 7 \to 8 \to 9 \to 10$. Note that Cell 6 is not used in TABLE 6-3. When considering flow-related risks, it is observed that the evacuees start to switch to the longest distance path—namely, $1 \to 2 \to 3 \to 6 \to 7 \to 8 \to 9 \to 10$. TABLE 6-4 shows that evacuees start to use Cell 6 at Time Step 5.

6.7 Summary

In this chapter, we propose a probabilistic modeling framework and a solution methodology to evaluate the impact of flow-related risks for developing reliable emergency evacuation plans. It is clear that during the evacuation process, high evacuation demand may potentially cause network degradation and influence later stages of evacuation operations. Thus, determination of a reliable evacuation plan is a critical issue not only for decreasing total evacuation clearance time but also for evaluating potential endogenously determined risks from the decision makers' and planners' perspectives. This problem is formulated as an extension of a cell-based, deterministic, optimal dynamic assignment model described in Ziliaskopoulos (2000) by adding constraints for capturing the impact of flow-related risks, as well as by defining a modified probabilistic objective function that is the sum of expected values of cell flows. The proposed model assumes that the cell capacity for a certain time step changes based on a probabilistic link capacity function that uses the cell flow in the previous time step as an input. One important, salient feature of the model proposed in this study is that it is not based on a mesoscopic/microscopic simulation model proposed by several recent studies dealing with similar evacuation problems. This is an important distinction because the use of a macroscopic model makes it possible to solve this stochastic optimization problem using well-known network flow algorithms and also to theoretically guarantee convergence to a system optimal solution as discussed later in this chapter.

One of our primary goals in this chapter is to draw attention to the issue of endogenously determined risks during the evacuation process. The proposed methodology and the case study can be used as a first step to theoretically show the importance of flow-related risks and their impact on departure schedule optimization in the evacuation process. Although our preliminary numerical results are limited by relatively small network and data availability, they still shed light on the reliability of evacuation plans when more realistic modeling assumptions such as flow dependent capacities are employed. For real-world applications of staged emergency evacuations, among several important issues that still need to be considered are background traffic when emergency situations emerge, optimal staging strategy, and estimation of flow-dependent capacity reduction functions based on historical breakdown records and related flow data.

7 SPECIAL STUDY: EMPIRICAL EVACUATION RESPONSE CURVE DURING HURRICANE IRENE IN CAPY MAY COUNTY, NEW JERSEY

Behavior analysis is a key component of evacuation modeling and is also critical for public officials deciding when to issue emergency evacuation orders. Such behavior is typically measured by an evacuation response curve that represents the proportion of total evacuation demand over time during evacuation.

In this chapter, we analyze evacuation behavior and construct an evacuation response curve based on traffic data collected during Hurricane Irene in Cape May County, New Jersey. Moreover, we also calibrated and compared the widely used S-curves with different mathematical functions and the state-of-art behavior models with empirical data. The results may benefit evacuation planning in similar areas.

7.1 Introduction

Hurricane Irene crossed and affected much of the east coast of the United States in August 2011. In New Jersey, flood waters covered roadways and transit lines. High-speed winds took down trees and power lines and caused significant damage and disruptions during the post-hurricane days. Fortunately, thanks to the proactive hurricane evacuation plans by state and local emergency authorities (PBS&J, 2007; Chien et al., 2006; Cape May County Emergency Management Communications Center, 2012), as well as early evacuation order declarations (Carnegie, 2012), the evacuation process in New Jersey was relatively smooth with little traffic disturbance. More than one million people, including at least 90% of the residents in the most impacted counties, left the New Jersey shore over 36 hours after the declaration of a mandatory evacuation order (State of New Jersey, 2012).

This study investigates the time-dependent evacuation demand during Hurricane Irene in Cape May County, the southern-most county of New Jersey, using empirical data. Evacuation demand rate is typically estimated by using a so-called response or mobilization curve, which estimates the proportion of total demand to evacuate within defined time intervals. These curves have been established either by expert judgment (Lewis, 1985; Radwan et al., 1985; Tweedie et al., 1986; Cova and Johnson, 2002) or by using mathematical models based on empirical evacuation behavior data (Fu and Wilmot 2004; Fu et al., 2006; Fu et al., 2006; Fu et al., 2007; Hasan et al., 2011). Because of the environmental, social, and geographic factors (Baker, 1991), evacuation response curves typically vary between different hurricane scenarios.

The objectives of this study are to construct the evacuation response curve in Cape May County, New Jersey, using observed data collected during Hurricane Irene and assess the state-of-art mathematical models with the constructed empirical response curve. Several features distinguish this study from previous ones.

First, New Jersey is not a hurricane-prone state such as the southeastern Atlantic or Gulf Coast states; Hurricane Irene was the first hurricane to directly hit the state since 1903. While a great deal of research focuses on hurricane-prone states (Wolshon et al., 2005), northern states along the Atlantic Coast receive insufficient attention. In addition, there is a high seasonal tourist population visiting and living along the New Jersey coast during the summer months. The total population of Cape May County can increase up to 850,000 in summer from 107,000 in winter (Cape May County Emergency Management Center, 2012). The behavioral patterns of residents have been well discussed in the literature (Baker, 1991; Whitehead et al., 2000; Wolshon et al., 2005; Dash and Gladwin, 2007); however much less is known about the empirical evacuation behavior of tourists (Baker, 2000). The data in this study may contribute to this emerging research area (Drabek, 1996; Matyas et al., 2011).

Second, when modeling evacuation response behavior, researchers base the available models (Lewis, 1985; Radwan et al., 1985; Tweedie et al., 1986; Cova and Johnson, 2002; Fu and Wilmot, 2004; Fu et al., 2006, 2007; Hasan et al., 2011) on empirical data from hurricane-prone states. However, whether such models are applicable to states with little hurricane experience is still unknown. In this study, the transferability of the models from hurricane-prone states is also discussed by calibrating and comparing a number of mathematical functions presented in the literature (Radwan et al., 1985; Tweedie et al., 1986; Cova and Johnson, 2002; Fu et al., 2006) with empirical data. The results may be valuable for evacuation modeling in similar areas.

Finally, the data used in this study come from automatic traffic counters rather than from traditional post-hurricane surveys. Compared with post-hurricane surveys, traffic data yield more realistic results and avoid the general "problem of recall" in social science (Dash and Gladwin, 2007). While much attention has been paid to hurricane evacuation behavior analysis, relatively few studies make use of real-world traffic data (Archibald and McNeil, 2012). With the increasing number of sensors being deployed on our roadways, this study also illustrates how to introduce empirical data sources for useful feedback on evacuation planning.

7.2 Literature Review

Research interest in evacuation response behavior started from empirical evidence of the population's response to emergency warnings. Baker (1979) reviewed four post-hurricane sample surveys and identified variables for predicting evacuation behavior. These variables were later summarized in five categories: risk level of the area, action by public authorities, housing, prior perception of personal risk, and storm-specific threat factors (Baker, 1991). More posthurricane surveys were conducted in late 1980s (FEMA, 2012). However, these posthurricane surveys were criticized as being not statistically reliable due to limited sample size or limited range of emergency situations. Relatively few studies provide concrete evidence on evacuation behavior during a particular type of emergency situation (Southworth, 1991).

Besides post-hurricane surveys, the stated preference surveys of potential evacuees are also commonly used in evacuation planning for areas with little prior evacuation experience. However, these surveys suffer from the usual problems associated with discrepancies between what people say they will do during hypothetical situations and what they actually do when confronted with the reality of the situation. “Those expected to evacuate may not, and those who do not need to evacuate often do” (Dash and Gladwin, 2007).

Given the problems associated with using either the revealed or stated preference survey data, some evacuation studies used subjective judgment based on expert experience. The sigmoid curves, also called S-curves, which were introduced by Lewis (1985), were generally used to represent the evacuation process. The evacuation rate (number of evacuees choosing to leave over time) starts slowly, then accelerates steeply, and finally slows down again (Baker, 2000). Depending on the speed, S-curves are classified as rapid, medium, and slow response as shown in FIGURE 7-1. A number of mathematical functions are used to exemplify the S-curves. Radwan et al. (1985) suggested the use of logistic distribution based on behavioral research. Tweedie et al. (1986) used Rayleigh distribution by consulting with experts in the state civil defense office. Cova and Johnson (2002) recommended the use of Poisson distribution based on queuing theory.

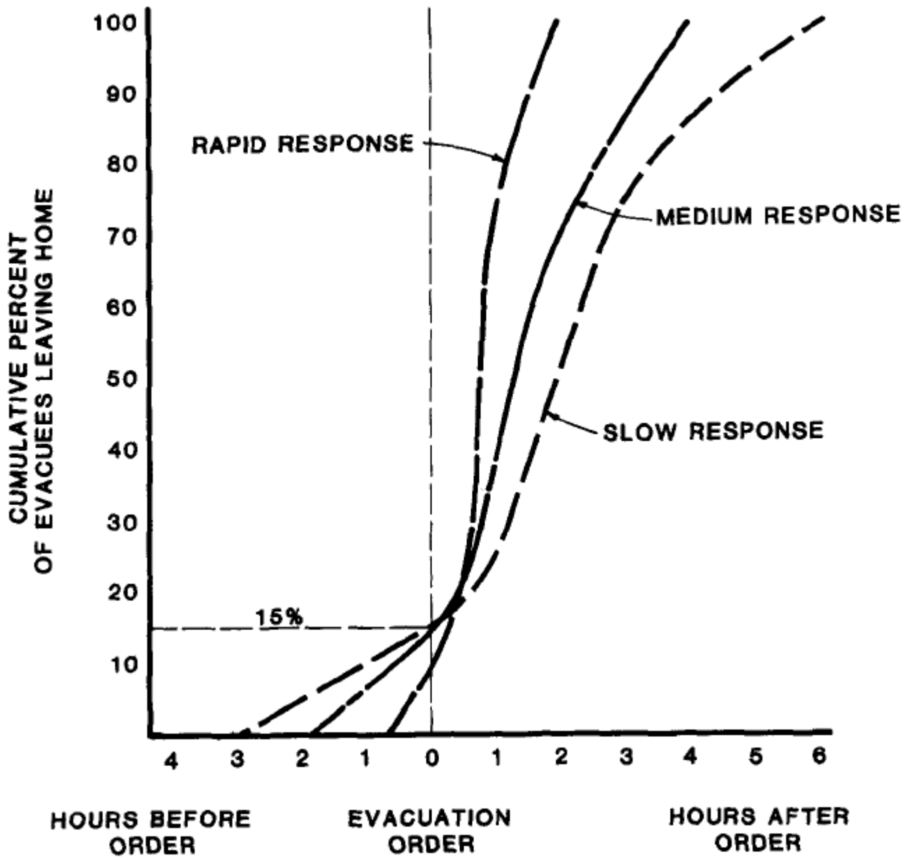


FIGURE 7-1 Evacuation Behavior Response Curves (Lewis, 1985)

Although widely adopted in hurricane evacuation plans of different states (FEMA, 2012), there are some disadvantages to using S-curves (Fu, 2004). One issue is that S-curves may not be able to model multiday evacuation with time-of-day variations in evacuation demand. The other issue is their subjectivity such that they reflect the analyst's perception but do not include hurricane characteristics or evacuation behavior. In order to remedy these drawbacks, a sequential logit model based on empirical data gathered during Hurricane Floyd (1999) was proposed first by Fu and Wilmot (2004) and later updated by Fu et al. (2006, 2007). The data included post-hurricane evacuation response behavior surveys and hurricane-specific characteristics such as wind speed, evacuation order, and so on. Recently, a random-parameter, hazard-based model was also proposed to understand household evacuation time behavior

(Hasan et al., 2011). While these models with behavioral variables contribute to a better explanation of the evacuation process, they are difficult to apply in evacuation planning because such variables cannot be accurately measured and predicted in future hurricane scenarios. A detailed review and comparison of S-curves and behavior models is presented in Yazici and Ozbay (2008).

7.3 Data

Recently, a number of studies attempted to use traffic data to analyze evacuation behavior. For example, Wolshon (2008) used volume data from automatic traffic counters in Louisiana to investigate empirical maximum evacuation traffic flow during Hurricane Katrina (2005) evacuation. Traffic data are generally preferable to data derived from post-hurricane evacuation surveys in terms of evacuation response curve modeling since the data provide more samples than post-hurricane surveys and since post-hurricane surveys are expensive to conduct and therefore have limited sample size (Southworth, 1991). Also, traffic volume data such as electronic toll collection (ETC) data or sensor data do not have the general "problem of recall" in social science, where people may have difficulty remembering their exact hour-by-hour decisions during a hurricane (Dash and Gladwin, 2007).

The data used in this study include hourly toll plaza volume counts on the Garden State Parkway (GSP). The GSP is a statewide corridor in New Jersey and is also the only major (limited-access) northbound evacuation route from the shore area of Cape May County. The Cape May toll plaza is a one-way, northbound (outbound) mainline barrier tollbooth located at mile marker 19.4 on GSP. In addition, the traffic data from the southbound (inbound) Great Egg toll plaza were also collected to check the possible "background traffic" (non-evacuating traffic).

(Please see a detailed definition in next section.) The Great Egg toll plaza is also a one-way mainline barrier tollbooth located at mile maker 28.8 on GSP.

The analyses included in this study are based on hourly traffic volumes from the Cape May toll plaza on GSP during August 24–28, 2011. This traffic primarily comes from Cape May peninsula and coastal barrier islands inside Cape May County, New Jersey. Thus, the traffic data can also be interpreted as samples of evacuees from all across Cape May County, New Jersey. The location and photos of both tollbooths and detailed evacuation process are shown in FIGURE 7-2.

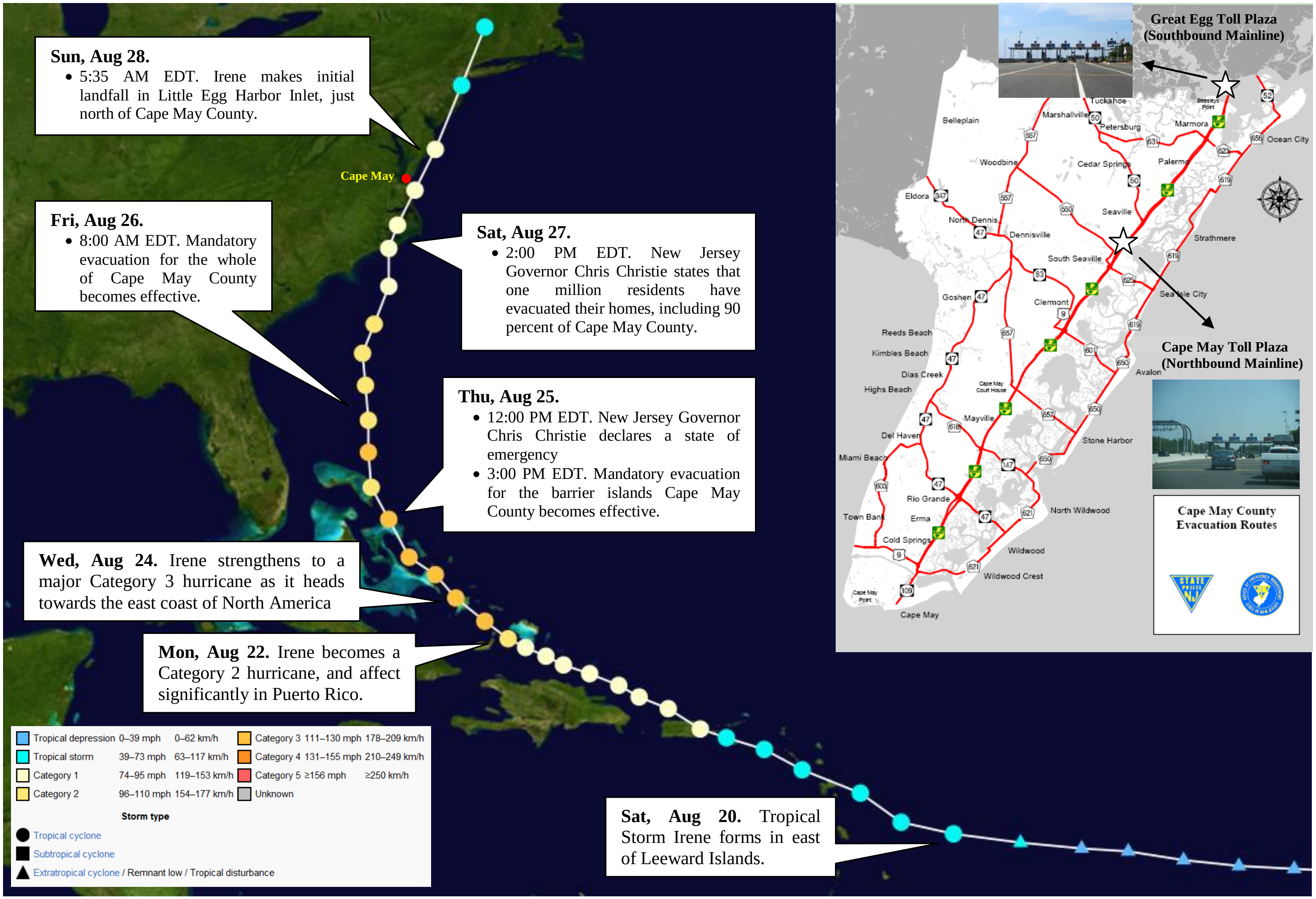


FIGURE 7-2 Toll Plazas on GSP and Hurricane Irene Evacuation Process

7.4 Evacuation Traffic and Demand Response Curve

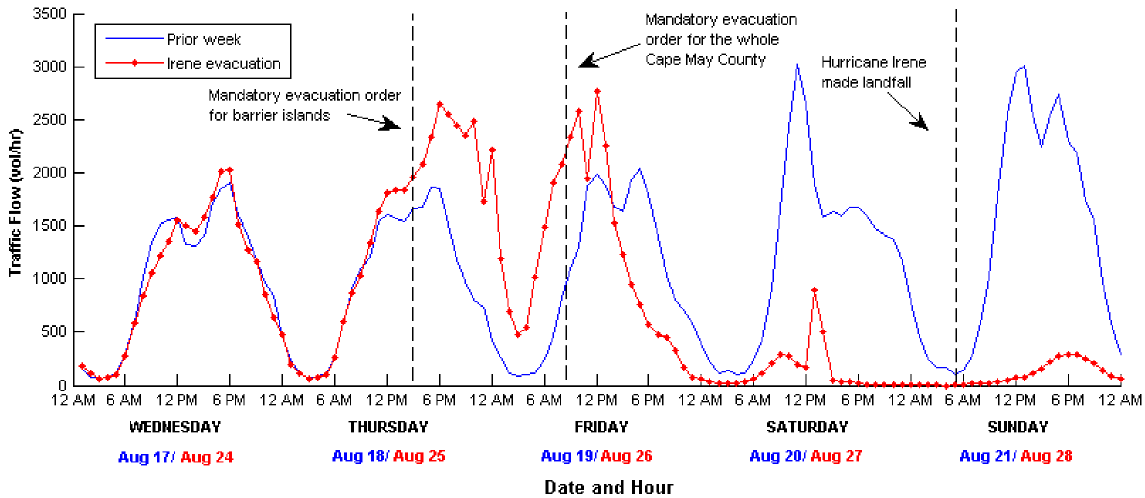
The temporal progression of Irene evacuation traffic is illustrated in FIGURE 7-3(a): the hourly traffic volume at Cape May toll plaza on GSP northbound from Wednesday, August 24, through Sunday, August 28. The time stamps of mandatory evacuation orders and Hurricane Irene landfall time are shown as dashed vertical lines. As a reference, traffic flows for the same days during the prior week are also included in FIGURE 7-3(a) to illustrate typical traffic conditions.

In order to construct an evacuation response curve, background traffic must be eliminated by following the suggestions of Urbanik (2000). “Background traffic consists of vehicles that are present during an evacuation but are not associated with permanent residents, transients, special facility populations, or voluntary evacuees” (Urbanik, 2000). Note the mandatory evacuation order of barrier islands issued on the afternoon of Thursday, August 25. FIGURE 7-3(b) shows the inbound traffic volumes at Great Egg toll plaza on GSP. It can be observed that there are no significant differences in traffic patterns between Thursday, August 25, and the same day of the prior week. Such a traffic pattern shows that people still commuted to Cape May County in the morning and possibly went back home as usual in the afternoon. Thus, when constructing the evacuation response curve, we eliminated the regular commuting trips from the traffic volume counts on Thursday, August 25. Such time-dependent commuting demand is assumed to have the same values as the same day of the prior week (Thursday, August 18). The significant reduction in traffic volume on Friday, August 25, in FIGURE 7-3(b) was caused by the restriction at the entrance. We assume that all of the traffic volume on Friday is due to the evacuation demand.

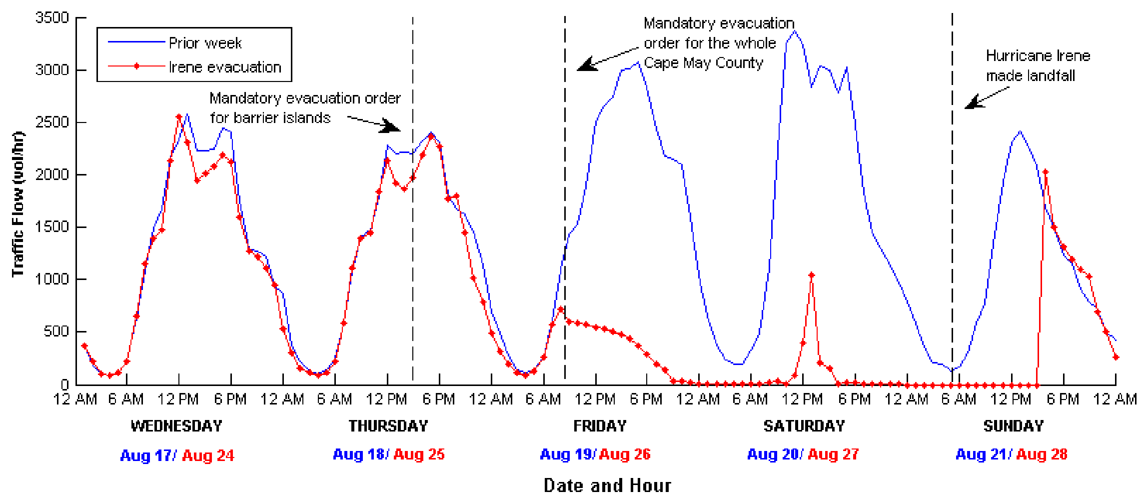
FIGURE 7-3(c) shows the evacuation response curve without background traffic derived from the Cape May toll plaza hourly traffic volumes during the evacuation. FIGURE 7-3(c) also includes the evacuation response curve with background traffic and the cumulative demand curve based on the same day of the prior week. The demand curves from the literature shown in FIGURE 7-1 are also added for comparison purposes.

The volume trend lines in FIGURE 7-3(a) show the Irene evacuation process in Cape May County. The process started around 9:00 a.m. on Thursday, August 25, when traffic volumes start to become significantly higher than the prior week's volumes. This increase in traffic volumes starts six hours before the mandatory evacuation order for the barrier islands. Approximately 6% of the evacuees had already evacuated by the time the mandatory evacuation order was issued. The major part of the evacuation, which comprised more than 85% of the evacuees, continued into the midnight of Friday, August 26. Less than 8% of the evacuees chose to evacuate on Saturday, August 27. In total, the duration of Irene evacuation in Cape May County was approximately 36 hours, and half of the total number of evacuees evacuated within 23 hours.

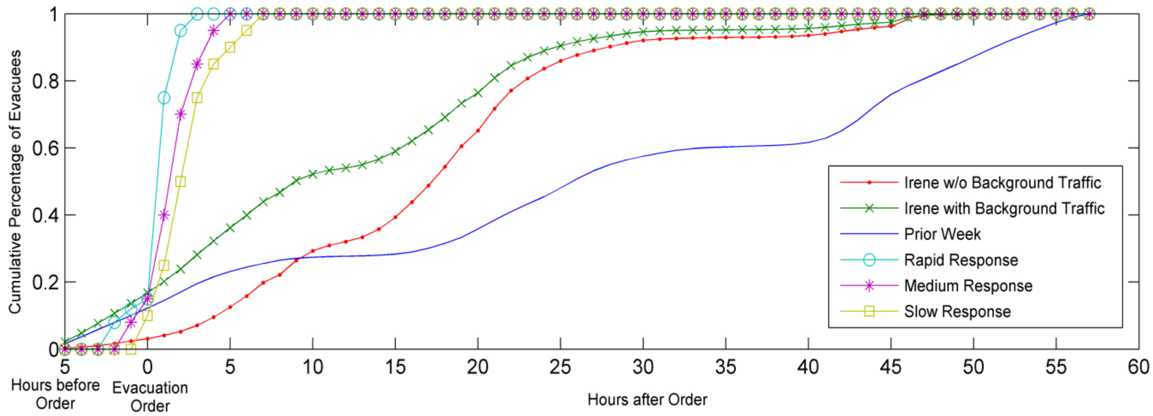
It can be observed in FIGURE 7-3(a) that the evacuees in Cape May County responded very quickly to the mandatory evacuation order. Traffic volumes increased significantly when the official mandatory evacuation order was issued. Two peak evacuation demand periods were observed around the start times of the mandatory evacuation for the shore areas (3:00 p.m., Thursday, August 25) and the whole county (8:00 a.m., Friday, August 26), respectively. The quick evacuation response behavior is also illustrated graphically in FIGURE 7-3(c). Sharp upward changes in the slope of the curve represent increases in the evacuation rate following the mandatory evacuation notices. Moreover, it should be noted that because the evacuation order was well before landfall of Hurricane Irene (approximately 72 hours ahead of the storm), the empirical curve is much more spread out than the theoretical ones in FIGURE 7-3(c).



(a) Outbound traffic counts from Cape May toll plaza on GSP



(b) Inbound traffic counts from Great Egg toll plaza on GSP



(c) Irene evacuation response curves and theoretical curves

FIGURE 7-3 Irene Evacuation Response Curves in Cape May County, New Jersey

The quick evacuation response behavior in Cape May County may have been due to the high tourist population. During the summer/hurricane season, more than 85% of the people in Cape May County are nonresidents. As stated in Drabek (1996), tourists exhibited a faster response rate than permanent residents. One of the reasons is that tourists, especially day-trippers, do not have the responsibility of protecting their residences. Moreover, tourists usually stay together; thus it is quick for them to gather and evacuate, while residents may be scattered, as discussed in Murray-Tuite and Mahmassani (2003, 2004). Tourists would instead first meet in a single location and then evacuate as a unit. This so-called household trip chain sequencing may delay residents' evacuation departure times.

Several other factors may also affect evacuation response behavior in Cape May County. One critical factor in evacuation behavior is evacuation experience. Residents of New Jersey, unlike those of the southeastern Atlantic Coast or Gulf Coast states, have relatively little or no hurricane evacuation experience. Prior literature (Baker, 1991;

Whitehead et al., 2000) found that people with no prior storm experience were more likely to evacuate than those with storm experience. For example, it was observed that without recent major hurricane history, 97% of people living in Pensacola and Pensacola Beach, Florida, evacuated before Hurricane Frederic in 1979 (Baker, 1991). Another factor that affects the evacuation response behavior is the location type (Baker, 1991). The people who live in rural areas, especially along the shore, are more prone to evacuate than those who live in urban areas. For example, prior to Hurricane Andrew (1992) making landfall in South Florida, people in the Florida Keys decided to leave earlier than necessary. However, many in urban areas in and around Miami decided not to leave at all, in part because of a perception of greater building safety in those areas (Drabek, 1996).

7.5 Comparative Assessment of Evacuation Response Models

The hourly volume data at the Cape May toll plaza of GSP during Hurricane Irene are extremely valuable for modeling evacuation behavior and comparing with other estimates and responses. As seen in FIGURE 7-3(c), significant differences are observed between the theoretical evacuation response curves (Lewis, 1985) and the empirical evacuation response curve from Hurricane Irene evacuation. In this section, four evacuation response models in the literature (Logit, Rayleigh, Poisson, and Sequential Logit) are reviewed and compared with the empirical evacuation response curve from Hurricane Irene.

7.5.1 Evacuation Response Model

7.5.1.1 Logit Function

The Logit function suggested by Radwan et al. (Radwan et al., 1985) is the most common approach to model the hurricane evacuation response curve. It is used in some of the developed evacuation modeling software tools such as TEDSS (Hobeika et al., 1994) and MASSVAC (Hobeika and Kim, 1998). The Logit function is shown in Equation 7-1:

$$P_t = 1/[1 + \exp[-\alpha(t - H)^2] \qquad (7\text{-}1)$$

Where P_t is the percentage of the evacuees departed by time t, and α and H are model parameters to be calibrated. α gives the slope of the cumulative traffic loading curve, and H is half loading time (the time when half of the vehicles in the system are loaded onto the highway network).

7.5.1.2 <u>Rayleigh distribution</u>

The Rayleigh distribution was suggested by local civil defense officials to describe evacuation departure time (Tweedie et al., 1986). The Rayleigh distribution is shown in Equation 7-2:

$$P_t = 1 - \exp[-0.5(t/\beta)^2] \qquad (7\text{-}2)$$

Where P_t is the percentage of evacuees departed by time t, and β is a parameter controlling the slope of the traffic loading curve.

7.5.1.3 <u>Poisson distribution</u>

The Poisson distribution is commonly used in queuing theory to describe the probability of n events occurring within a given time period. The distribution was proposed in Cova and Johnson (2002) to model a random evacuation departure process. Poisson distribution is shown in Equation 7-3:

$$P_t = \exp(-\gamma)\sum_{i=0}^{\lfloor t \rfloor}\frac{\gamma^i}{i!} \tag{7-3}$$

Where P_t is the percentage of the evacuees who have departed by time t, and γ is a parameter controlling the slope of the traffic loading curve.

7.5.1.4 *<u>Sequential Logit</u>*

A sensitivity analysis of evacuation probabilities was proposed in Fu and Wilmot (2004) and later improved by Fu et al. (2006, 2007). In the model, each random utility function U_i^n (utility of a household not evacuating at time t) and U_t^e (utility of a household evacuating at time t) are assumed to be composed of a systematic component V_t and an error term ε_t (i.e. $U_t^n = V_t^n + \varepsilon_t$ and $U_t^e = V_t^e + \varepsilon_t$). Also, the utility differences $U_t^n - U_t^e$ are assumed to be independently and logistically distributed. Then, the probability of a household evacuating at time t, given that it has not evacuated earlier, is shown in Equation 7-4:

$$P(t)_{e/n} = \frac{\exp(U_t^e)}{\exp(U_t^n) + \exp(U_t^e)} = \frac{\exp(V_t)}{1 + \exp(V_t)} \tag{7-4}$$

$$V_t = U_t^e - U_t^n = -2.292 + 1.018 * TOD1 + 2.123 * TOD2 + 1.949 * TOD3 + 2.111 * Order1$$
$$+ 2.356 * Order2 + 0.019 * Speed - 1.748 * Ln(T)$$

The linear formulation was calibrated and validated in Fu et al. (2007), where

TOD : the time of day—1 for early morning (6:00 a.m. to 10:00 a.m.), 2 for middle day (10:00 a.m. to 4:00 p.m.), and 3 for late afternoon (4:00 p.m. to 8:00 p.m.).

$Order$: evacuation order—1 for voluntary, 2 for mandatory.

$Speed$: hurricane speed (mph)

$Ln(T)$: the natural logarithm of time T to hurricane landfall.

7.5.2 Model Comparison and Discussion

In order to compare the capabilities of the described evacuation response models, in terms of fitting the empirical data from Hurricane Irene, the first challenge is to determine the parameter settings of each model. The values of parameters of each model are not fixed for different hurricane scenarios due to environmental, geographical, and social factors (Baker, 1991). For example, as stated in Lindell and Pratel (2007), $\beta = 40$ provided the best fit for Rayleigh distribution of the empirical data in Tweedie et al. (1986), while the response curve in Hobeika and Kim (1998) and Southworth and Chin (1987) was equivalent to a Rayleigh distribution with $\beta =$ 45 and 74, respectively.

In this section, we first calibrate the parameter settings of each described model with empirical data from Hurricane Irene. Then the results of the calibrated models are compared to find the best-fit model. Some recommendations and limitations of the evacuation response models are also discussed.

7.5.2.1 Statistical Measure

The root mean square error (RMSE) is used in this study to measure the difference between the model result and empirical data. RMSE is a frequently used measure of how close a fitted line is to data points. Specifically, in this study RMSE is the difference between the result of each model and empirical data. It can be mathematically represented as follows:

$$RMSE(\hat{s}) = \sqrt{E((\hat{s}-s)^2)} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{s}_i - s_i)^2}{n}} \tag{7-5}$$

Where $\hat{s}$ is the fitted result from each model, s is the empirical data from Hurricane Irene, and n is the number of time intervals (hours) in each S-curve. RMSE is thus the average distance of the empirical evacuation response curve from the fitted result of each model. The smaller the RMSE, the better the fit of the model is to the empirical data.

7.5.2.2 Model Calibration and Comparison

In this study, in order to calibrate each evacuation response model with empirical data, first the results of the model are calculated with different parameter settings. Then RMSE values are used to compare each model result with the empirical data, as shown in FIGURE 7-4. The parameter setting with the minimum value of RMSE is chosen as the calibrated one. Because the sequential Logit model was calibrated and validated with empirical data from Hurricane Floyd and Hurricane Andrew, the parameter settings given in Fu et al. (2007) are directly used in this study.

FIGURE 7-4 shows that improperly calibrated evacuation response models can have significant prediction errors. The average errors of all three models fluctuate from less than 10% to as much as 60% in the Poisson distribution. The recommended parameter settings are $\alpha \in [0.1, 0.3]$ for the Logit function, $\beta \in [15, 20]$ for the Rayleigh distribution, and $\gamma \in [15, 20]$ for the Poisson distribution.

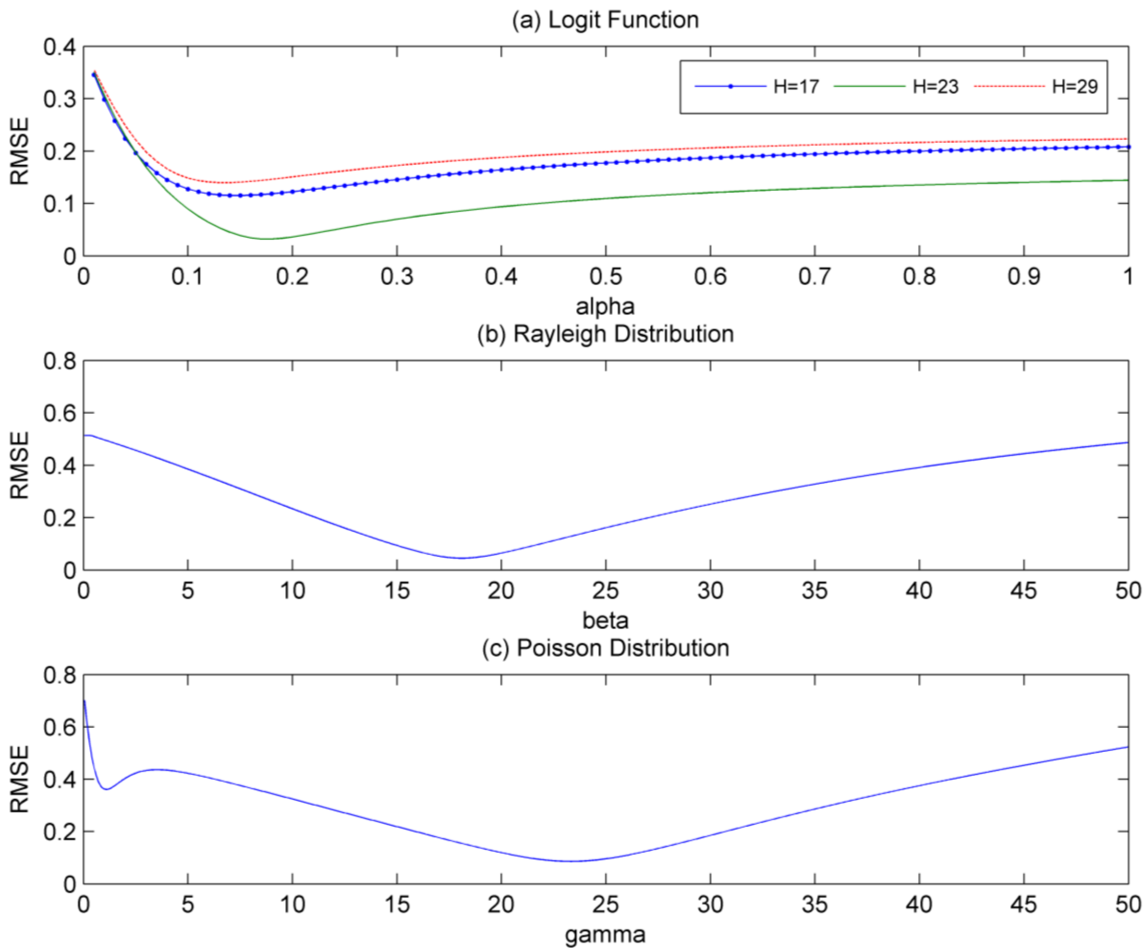


FIGURE 7-4 The Parameter Calibration of S-curve Distributions

As seen in FIGURE 7-4, the Logit function yields a better fit compared with the other two distributions. As described above, the half loading time (H) of Hurricane Irene evacuation is 23 hours. When $H = 23$, it can be observed that the curve based on the Logit function quickly converges and become stable. RMSE is between 15% and 20% on average, while less than 5% at its minimum. FIGURE 7-5 graphically shows the difference between each calibrated evacuation response model and the empirical response curve obtained from traffic data collected prior Hurricane Irene. The Logit and Rayleigh distributions fit empirical data better. The RMSE of the Logit and Rayleigh distributions are 3.21% and 4.77%, respectively. As a symmetric distribution, the Logit function fits the middle part of the empirical curve very well, as shown between Hours 20 and 30 but underestimates the demand during the evacuation process following the mandatory evacuation order (between Hours 10–20 and 30–40). While the Rayleigh distribution overestimates the demand during the early evacuation process (the first 24 hours), it generally underestimates the tail of the empirical curve.

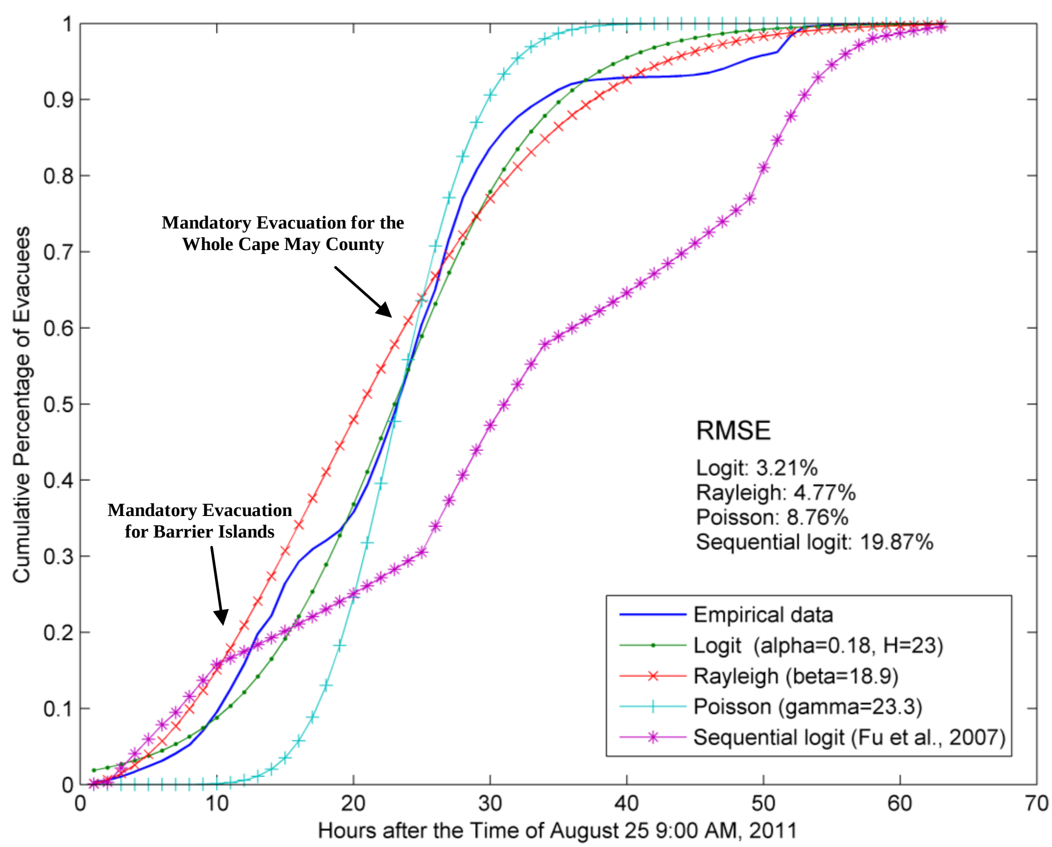


FIGURE 7-5 Comparison of Calibrated Models with Observed Data

However, the Logit function may increasingly misrepresent the empirical data with improper parameter settings of H, given the calibrated parameter α. As described in Yazici and Ozbay (2008), α can be interpreted as the parameter that controls the behavior of evacuees, while H determines the half evacuation loading time, or so-called clearance time ($2H$). The Logit density function is a symmetric distribution (Lindell and Prater, 2007), and therefore given the value of parameter α, different values of H can shift the S-curve in the horizontal direction and affect the calibration result. It can be observed in FIGURE 7-4 that the Logit function with $H = 23$ fits better with the empirical data compared to the other two models (where it is known that the half loading time is 23 hours during Hurricane Irene evacuation). However, the half loading time is difficult to predict due to specific hazard conditions and geographical and social factors. A sensitivity analysis with different values of H is suggested when applying the Logit function in the context of hurricane evacuation planning.

7.5.2.3 *Discussion of Results*

In summary, in part because of the quick response behavior of evacuees, the response curve during the multiday Hurricane Irene evacuation process can still be considered a general S-shape, instead of multi-S-shapes, for Cape May County, New Jersey. The widely used S-curve models with the Logit and Rayleigh functions also fit the empirical data well.

Moreover, the recommended parameter settings of S-curves for the case of Irene evacuation are also compared with those of other empirical studies. As summarized in Lindell and Pratel (2007), only a modest amount of empirical data has been used for calibrating and comparing evacuation response curves recommended by Lewis (1985), as shown in FIGURE 7-1. A recent study by Koshute (2012) evaluated Logit function vis-à-vis empirical evacuation response curves observed in six different hurricane scenarios. The results showed that a Logit function with the parameters $\alpha \in [0.4,0.5]$ fit better in general for all hurricane scenarios. Such parameter values are slightly higher than the recommended setting ($\alpha \in [0.1,0.3]$) for Irene evacuation. However, the model parameter settings of empirical studies may also vary significantly, probably due to different environmental, geographical, and social factors. For example, $\beta = 117$ and 181 provided the best fit for the Rayleigh distribution for empirical evacuation departure time distributions of Texas Gulf Coast residents leaving from home or work (Lindell and Prater, 2007). The parameter settings were significantly different than our recommended range ($\beta \in [15,20]$).

The state-of-art Sequential Logit model may not be transferable to other areas with little hurricane evacuation experience. FIGURE 7-5 shows that the calibrated Sequential Logit model does not perform well compared with empirical data from Hurricane Irene in New Jersey. One possible explanation is that, as concluded by Hasan et al. (Hasan et al., 2012), the parameters of the evacuation choice models are only transferable over different hurricane contexts in similar hurricane-prone regions. The studies that modeled evacuation behavior, including the recent studies about the transferability of such models (Hasan et al., 2012; Murray-Tuite et al., 2012; Fu et al., 2006), are usually based on empirical data from hurricane prone regions including Florida and the Gulf Coast states. Obviously, such studies are not usually conducted due to insufficient data in northern states such as New Jersey that have little hurricane experience. It may also be argued that while regions such as New Jersey are not at high risk for hurricanes, areas with medium or low risks are sometimes more critical and may have significant damage potential due to insufficient planning and experience. Sound behavior models will still be required to bridge the gap between hurricane-prone states and other states with little hurricane experience.

Clearly, with the increasing number of traffic sensors being deployed throughout our transportation system, this study is also a demonstration of the possible use of empirical data sources for important feedback on the evacuation planning process. Compared with post-hurricane surveys, data from automatic sensors have several advantages, including large sample size, low cost, and wide spatial distribution. Such data may provide benefits for other applications, such as comparison between evacuation traffic patterns and regular weekend traffic patterns, which was studied by Archibald and McNeil (2012). Interestingly, they used sensor data and found that the evacuation traffic during Hurricane Irene in Delaware was very similar to the regular weekend traffic. Such a finding is reasonable for areas with a high tourist population.

The question of the similarity of hurricane evacuation traffic and the usual weekend shore traffic can also be studied using the observed data in this study. In this case, we compared the traffic data from the weekends before (Sunday, August 21) and after (Labor Day, Monday, September 5) the hurricane with evacuation data (Friday, August 26). FIGURE 7-6 shows that the evacuees tended to be more risk averse, with a 3- to 4-hour earlier departure time compared to regular weekends and holidays. The comparison shows that evacuation traffic is not totally unpredictable and may benefit from traffic management, especially for those without prior emergency evacuation experience. However, this analysis is beyond the scope of this study and may be a subject for future work.

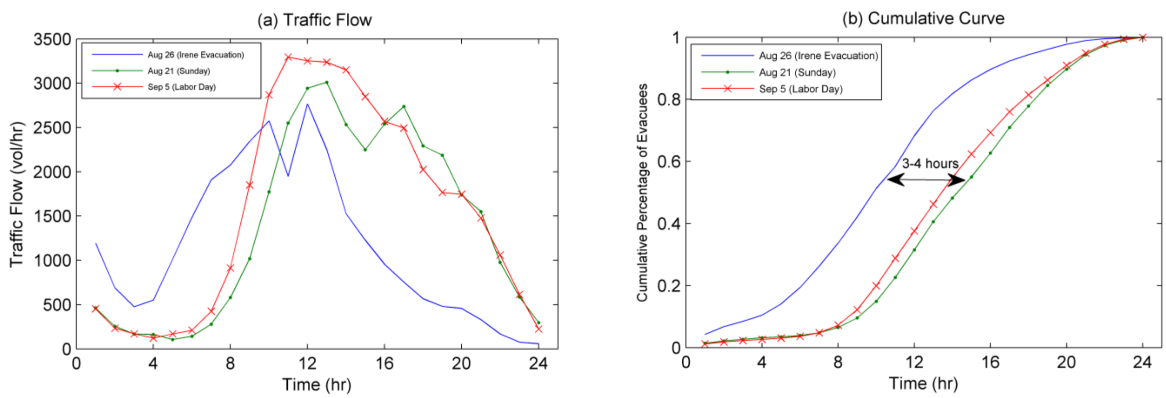


FIGURE 7-6 Traffic Patterns during Irene Evacuation and Weekends

7.6 Summary

This study analyzed the evacuation response curve during Hurricane Irene in Cape May County, New Jersey. The hourly toll plaza volume counts on the Garden State Parkway (GSP) were used for the analyses. Compared with traditional post-hurricane surveys, traffic volume data had several advantages, including large sample size and avoiding the problem of recall in social science. The widely used so-called S-curves with different mathematical distributions (Logit, Rayleigh, and Poisson) and state-of-art behavior model (Sequential Logit) were calibrated and compared with observed empirical data. The major conclusions of this study were as follows:

(a) The evacuees in Cape May County responded very quickly to the mandatory emergency order. Traffic volumes increased significantly when the official mandatory evacuation order was issued.

(b) The evacuation response curve was generally S-shaped with sharp upward changes in slope followed the issuance of mandatory evacuation notices. The sharp upward changes in the curve represented the quick evacuation response behavior observed during Hurricane Irene.

(c) The observed evacuation response behavior of the evacuees may have been partly caused by the high tourist population. Other factors such as little to no prior hurricane experience and limited evacuation routes may have also affected the observed evacuees' behavior.

(d) When comparing different evacuation response models, the calibrated S-curves obtained using the Logit and Rayleigh functions were observed to fit the empirical data better. The better fit of S-curves was partly due to the quick response behavior of evacuees.

(e) The Sequential Logit model did not perform well when compared with empirical data. This is possibly due to the fact that state-of-art behavior models based on empirical data from hurricane-prone regions may not be transferable to states such as New Jersey with little or no previous hurricane experience.

(f) The empirical data can also be used for comparative analysis of traffic patterns during evacuation periods and regular weekdays/weekends. Our preliminary results showed that the evacuation traffic pattern was similar to that of typical outbound traffic from the shore areas at the end of a summer weekend but with a 3- to 4-hour earlier departure time.

The observed data from Hurricane Irene and calibrated parameter settings of evacuation response models may benefit evacuation planning in areas with circumstances similar to those of Cape May County, New Jersey. However, it should be noted that the findings of this study cannot be generalized since they are based on the analysis of a single set of data of evacuation behavior from a specific hazard condition in a particular area. Sensitivity analysis is recommended in other areas based on the calibrated models. Moreover, in order to have a reliable evacuation response model, more empirical data from different hurricane scenarios are required. This data should be used to better calibrate and compare current state-of-practice and state-of-art evacuation response models. In addition, when using traffic data for evacuation response behavior analysis, one limitation of such data is that the traffic volume may come from different counties or regions and cannot be easily differentiated. In other words, the data may be a mixture of data from all evacuees from different counties or regions with separate evacuation orders and geographic and social circumstances. However, such data could still benefit local highway agencies in terms of understanding similar hazard conditions for emergency traffic management.

Moreover, compared to evacuation modeling, behavior analysis is a much more fundamental issue for better understanding of the evacuation decision-making process. In this study, we offer several tentative explanations for quick response behavior, which may be in part caused by an easily mobilized tourist population, lack of previous hurricane evacuation experience, and/or the nature of the location, which in this case was a rural area with limited evacuation routes. However, such hypotheses still need additional rigorous tests supplemented with individual information from a large sample of evacuees. The current traffic data do not contain such data. A possible future work could conduct evacuation behavior surveys among residents and tourists in Cape May County, New Jersey.

8 CONCLUSIONS AND FUTURE RESEARCH

8.1 Conclusions

In this dissertation, transportation emergency planning and operations were studied by integrating emerging data sources along with new computational and mathematical tools. In this vein, an effort was made to enhance current state-of-practice evacuation planning tools and apply such tools to practical issues related emergency conditions. The dissertation focused on three areas: emergency evacuation modeling, critical infrastructure identification, and analysis of trip demand behavior under hurricane evacuation conditions.

8.1.1 Emergency Evacuation Modeling

An efficient evacuation planning model is of the utmost importance in determining evacuation times, identifying critical locations in the transportation network, and assessing traffic operations strategies and evacuation policies. In this dissertation, an evacuation modeling platform that employs a widely available regional transportation planning tool is proposed as the basic modeling platform. In order to address the static nature of this traditional planning model, a pseudo-dynamic procedure that entails running consecutive traffic assignments with short time intervals was proposed. The traffic was dynamically updated for each time interval by considering residual demand from the previous interval. The proposed procedure was tested with a variety of scenarios using a developed regional travel demand model in north New Jersey. The details of this modeling platform can be found in Ozbay et al. (2012)

The customized regional planning tool is a suitable platform to model transportation emergency evacuation. However, due to its static nature, this platform cannot capture the impact of uncertain events in the emergency evacuation process. Because of the high volume of evacuation traffic and stress-driven behavior, uncertain events such as traffic accidents or disabled vehicles are more prone to happen and cause significant delays. This dissertation proposed an analytical framework along with the efficient solution methodology in Li and Ozbay (2012). Instead of only considering exogenously determined risks, such as flooding damage, in current studies of evacuation modeling, the objective of this novel framework was to evaluate the impact of endogenously determined risks in order to develop reliable emergency evacuation plans. We incorporated the probability function of the endogenously determined risks into a cell-based macroscopic evacuation model. A network flow algorithm based on the sample average approximation approach was used as part of the solution procedure. Finally, a sample network was used to demonstrate the salient features of the proposed stochastic model and solution procedure.

8.1.2 Critical Infrastructure Identification

Evacuation modeling platform and behavior analysis are critical for emergency preparedness. Link criticality evaluation is an important problem in hazard mitigation plans for public officials. However, this type of analysis presents numerous challenges in terms of accurately capturing the impacts of highly stochastic hazard events. An analytical framework and an efficient solution procedure were proposed by Li and Ozbay (2012) for link criticality evaluation, which considered the impact of day-to-day degradable transportation network conditions. Link capacity is considered a multi-status variable, and a sampling technique was used to generate realizations of transportation network capacity values. With different capacity realizations, traffic demand was repeatedly assigned on the regional planning model network, and the assignment results were measured with multiple criteria and analyzed using several statistical indices. A case study based on a portion of the New Jersey roadway network was presented to verify the proposed approach.

Besides using simulation techniques to determine the critical links along evacuation routes, we are currently working on analyzing empirical travel time data during Hurricane Irene (2011) and Sandy (2012) to identify spatiotemporal patterns of link failures. The preliminary results show that the bottlenecks during Irene evacuation were generally located in the merging areas. A detailed analysis that considers the idea of ramp control in emergency management, especially during hurricane evacuation, is underway.

8.1.3 Analysis of Demand Behavior under Hurricane Evacuation Conditions

Behavioral analysis is a key component of any evacuation modeling effort and is also critical for public officials in deciding when to issue emergency evacuation orders. Such behavior is typically captured by an evacuation response curve that represents the proportion of total evacuation demand over time. In this dissertation, evacuation behavior was analyzed and an evacuation response curve was estimated based on traffic data collected during Hurricane Irene (2011) in Cape May County, New Jersey (see Li et al., 2013). An initial observation of the empirical demand data showed that the evacuation response followed an S-shape with sharp upward changes in slope following the issuance of mandatory evacuation notices. Then, distinct evacuation demand curves were calibrated using different mathematical approaches proposed in the literature along with empirical data Moreover, the results showed that the calibrated S-curves with Logit and Rayleigh functions fit empirical data better than others. The behavioral analysis and calibrated evacuation response models based on this recent hurricane evacuation event in New Jersey may benefit evacuation planning efforts in similar areas.

Besides studying demand behavior under emergency conditions, we are currently working on developing a systematic methodology to understand overall evacuation demand, destination type choice, and route choice decisions during Hurricanes Irene (2011) and Sandy (2012) in New Jersey. In the project of modeling disaster operations from an interdisciplinary perspective in the New York–New Jersey area, we will consider both transportation and social and other relevant factors such as actions of agencies dealing with emergency operations. Original data from past hurricanes will be used to estimate and calibrate the models, as well as new traffic data from Hurricane Irene (2011) and Sandy (2012), which were two major hurricanes in the northeast areas, thereby allowing us to understand the determinants of different behavioral dimensions during hurricane evacuation.

8.2 Future Research

In the future, the focus of research presented in this dissertation can be broadened to cover the general field of mitigation and planning for extreme events, including not only natural or man-made disasters but also special events such as festivals and games. We are particularly interested in utilizing technological innovations such as social media and smart vehicle technologies to collect driver behavior data and evaluate transportation management strategies during these special events.

8.2.1 Transportation Management for Special Events

Disasters are extreme and rare events. However, some planned special events that draw large crowds such as football games are similar to disasters. In fact, many college football games are attended by 100,000 spectators or more, and the associated congestion in towns and small cities can overwhelm the local highway system on game days. Such special events require developing and deploying operational strategies, traffic control plans, and technologies to control traffic and share real-time information. It will be interesting to analyze and apply some hurricane traffic management strategies, such as contraflow operations, signal control, and ramp management, for special events. In addition, the transportation management for special events may be considered as preparation exercises for natural or man-made disasters, and the experience may benefit more serious emergency management operations.

8.2.2 Driver Behavior during Uncertain Events

Understanding human behavior and what drives people's choices has been a subject of research in the fields of economics, psychology, transport, and beyond. The analysis of drivers' reactions to uncertain events, including natural disasters or incidents/accidents, has been limited partly due to the type of data commonly collected. However, current technological innovations such as social media and smart vehicle technologies provide opportunities to collect data of driver behavior under uncertain events. It is interesting to measure drivers' attitudes towards uncertain and unreliable routes. Such analysis may also benefit emergency management during natural or man-made disasters.

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