USDOT Region V Regional University Transportation Center Final Report

NEXTRANS Project No 019PY01

Integrating Supply and Demand Aspects of Transportation for Mass Evacuation under Disasters

By

Srinivas Peeta, Principal Investigator
Professor of Civil Engineering
Purdue University
peeta@purdue.edu

and

Yu-Ting Hsu
Graduate Research Assistant
School of Civil Engineering
Purdue University
yhsu@purdue.edu

Report Submission Date: October 15, 2009

DISCLAIMER

Funding for this research was provided by the NEXTRANS Center, Purdue University under Grant No. DTRT07-G-005 of the U.S. Department of Transportation, Research and Innovative Technology Administration (RITA), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

USDOT Region V Regional University Transportation Center Final Report

TECHNICAL SUMMARY

NEXTRANS Project No 019PY01 Final Report, October 2009

Integrating Supply and Demand Aspects of Transportation for Mass Evacuation under Disasters

Introduction

This study seeks to address real-time operational needs in the context of the evacuation response problem by providing a capability to dynamically route vehicles under evacuation, thereby being responsive to the actual conditions unfolding in real-time in the traffic network, both in terms of the evolving traffic patterns (demand-side) and the available road infrastructure in the aftermath of the disaster (supply-side). A key aspect in evacuation operations which is not well-understood is the interplay between route choice behavior and its effect on traffic and supply dynamics (i.e., composition of evacuation traffic, changes in roadway capacities, etc.). Evacuation traffic has historically been quantified with descriptive surveys characterizing the behavioral aspects from social or psychological contexts. Integration of these behavioral aspects into traffic and/or supply-side models has been limited. This study seeks to address such integration for generating realistic and effective evacuation strategies by focusing on developing behavioral models for no-notice mass evacuation. They include: (i) an evacuation participation decision model that determines whether an individual or a group of individuals would evacuate at the current time in a disaster context, and (ii) an evacuation route choice model that determines the routes taken by individuals or groups of individuals after they take a decision to evacuate.

Under a comprehensive framework which integrates the management of demand- and supply-side components, this study focuses on the modeling of behavior under no-notice evacuation, which has rarely been emphasized in previous studies, especially in terms of the fundamental understanding of the effect of evacuation behavior upon information strategies and vice versa. An understanding of evacuee behavior in terms of their response to the changing environment and control strategies by emergency management agencies (EMAs) throughout the evacuation process is critical for both the planning and operational contexts. For operational control, this effectiveness depends significantly on the level of behavioral understanding of the demand-side problem. Methodological challenges arise from uncertainty and randomness in disaster dynamics and evacuees' decision process under extreme time pressure.

Findings

The modeling of the behavior related to evacuation participation and route choice at an aggregate level must accommodate the following considerations:

(i) Key factors, such as perception of risk, that involve subjective interpretation rather than objective assessments and/or observable measurements.

(ii) During the evacuation process, the information about disaster, traffic conditions and other important issues that may entail linguistic description; for example, "the disaster is severe" or "may be seriously congested", rather than numerical measurements.

(iii) At an aggregate level, the perception of environmental factors may vary across individuals in a traffic assignment zone (the unit of aggregation) based on personal attributes, which highlights the issue of heterogeneity for model consistency.

The proposed model adopts discrete choice theory, which is commonly employed in modeling choice behavior. However, to address the above issues, fuzzy set theory is further incorporated into the model within the structure of the mixed logit model.

Individual behavior under the context of evacuation problem can be viewed as a hierarchical one. First, an individual makes the decision whether to evacuate at a certain time stage or not (that is, to postpone the decision to evacuate to a future time stage). The decision at this level primarily depends on:

(i) perceived risk, which is derived from the information about the disaster.

(ii) recommendation or order to evacuate (or not to evacuate) at the current time stage from the EMA.

(iii) herding behavior (or peer effect), which is observed in that people tend to follow the decisions of others.

(iv) state dependence, which is due to non-evacuation decisions in previous time stages, from the perspective of evacuation operation. That is, if an individual does not evacuate in the last time stage, his/her decision to evacuate or not in the current time stage will be affected by his/her previous decision. Further, as the number of non-evacuation decisions increase, there is more pressure on an individual to make a decision to evacuate in this time stage.

Second, an individual makes a decision on which route to take to a safe place. Under no-notice evacuation, due to the time pressure issue and the disaster characteristic, an individual does not deliberate on the destination of the evacuation trip, but selects a route from among several routes which lead him/her to the nearest safe places. In this context, the key variables influencing the decision at the second level include:

(i) estimated travel time from the information available on traffic conditions.

(ii) perceived risk on the route based on the disaster's potential impacts or the possibility of link failure.

(iii) recommendation or guidance from the EMA about the route to take.

(iv) freeway bias, which has been observed from previous stated preference surveys that indicate that the route through freeway is considered more reliable and preferred, though the reported travel time on the route is more than that on other arterials. Freeway bias is defined as the proportion of the length on freeway to the total length of the route.

Recommendations

In the literature, existing studies related to evacuation have predominantly focused on either the supply-side solutions or sought to qualitatively describe behavior using observed traffic patterns in actual disasters. This study seeks to link these two elements, formally acknowledging that such linkage is necessary for effective evacuation strategies, in the context of no-notice evacuation.

For no-notice evacuation, to the best of our knowledge, behavior issues have not been empirically and quantitatively studied in the literature. To address the inadequacy, this research proposes a model that: (i) investigates zonal behavior in considering practical implementation and data availability under no-notice evacuation operations at an aggregate level, and (ii) highlights the importance of understanding behavioral issues/phenomena under evacuation and provides a platform for designing behavior-robust information strategies for more effective dynamic routing.

This study reviews the characteristics of the mass evacuation problem from the viewpoints of disaster, demand and supply. Based on the problem characteristics, discrete choice models are developed by incorporating a fuzzy logic approach into the structure of mixed logit models to account for: (i) individuals' subjective interpretation and perception under time pressure, and (ii) the heterogeneity across the individuals in an aggregate manner. Simulation experiments are conducted to test the prediction capability of the proposed models. The results indicate the ability of the models to interpret the evacuation behavior from observable variables at an aggregate level.

In the context of real-world deployment, this study proposes aggregate behavior models based on data availability. However, the need for insights on human behavior under different kinds of disaster situations necessitates field surveys at a disaggregate (individual) level. Additionally, in the absence of field data, most studies on the modeling of mass evacuation rely on simulation, resulting in trade-offs in terms of realism. Hence, future research that develops robust behavior models at the individual level can be used to strengthen the behavior modeling components within a simulation framework. Based on the choice models proposed in this study, the next step in the research would be on constructing a behavior-based control model to develop more efficient evacuation strategies for EMAs to manage the system effectively from the supply side.

Contacts

For more information:

Srinivas Peeta
Principal Investigator
Civil Engineering
Purdue University
peeta@purdue.edu

NEXTRANS Center
Purdue University - Discovery Park
2700 Kent B-100
West Lafayette, IN 47906

nextrans@purdue.edu
(765) 496-9729
(765) 807-3123 Fax

www.purdue.edu/dp/nextrans

USDOT Region V Regional University Transportation Center Final Report

NEXTRANS Project No 019PY01

Integrating Supply and Demand Aspects of Transportation for Mass Evacuation under Disasters

By

Srinivas Peeta, Principal Investigator
Professor of Civil Engineering
Purdue University
peeta@purdue.edu

and

Yu-Ting Hsu
Graduate Research Assistant
School of Civil Engineering
Purdue University
yhsu@purdue.edu

Report Submission Date: October 15, 2009

ACKNOWLEDGMENTS

The authors acknowledge feedback in the subject domain from the members of the study advisory committee of the cost-share project funded by the Joint Transportation Research Project (JTRP), Purdue University.

TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1. INTRODUCTION

Mass evacuation is necessary for immediate or potential life-threatening danger caused by natural or man-made disasters; population in a defined affected area has to be evacuated to places of safety. The major challenge of the evacuation problem arises from a surge of traffic demand, which might exceed the capacity of an existing roadway system and result in congestion or even the gridlock of the network. The purpose of evacuation operations is to avoid such unfavorable mobility situations and/or to lessen the related loss of life and property. The improvement of the network performance depends on the efficient management of the demand-supply problem of the evacuation network. Most existing evacuation management approaches address the problem from the supply-side, emphasizing network design and capacity enlargement, such as contra-flow lanes (Tuydes and Ziliaskopoulos, 2006; Kalafatas and Peeta, 2007). By contrast, demand-side issues have been largely ignored or simplified by assuming a pre-determined origin-destination pattern and/or a pre-determined compliance rate in most previous studies. The research on evacuation behavior has mostly been conducted in social or psychological contexts, while quantitative analysis is comparatively sparse (Lindell and Prater, 2007).

The demand-supply patterns of the evacuation network are dependent on the disaster characteristics. From a disaster perspective, the evacuation problem can be categorized into short-notice and no-notice disasters. The key factors for this categorization are the predictability of a disaster's occurrence and lead-time (which directly affects the issuance of the evacuation notice). Short-notice disasters, such as hurricane, flooding, etc., are comparatively more predictable and provide a lead-time of between 24-72 hours (Wolshon et al., 2002). The lead-time allows both evacuees and emergency management agencies (EMAs) to be better prepared for the evacuation operations. By contrast, a no-notice evacuation takes place immediately after the unexpected occurrence of a disaster (Anon, 2005), incurring a higher level of operational complexity. Examples of such disasters include earthquake, terrorist attack, hazardous material release, etc.

Under a comprehensive framework which integrates the management of demand- and supply-side components, this study focuses on the modeling of behavior under no-notice evacuation, which has rarely been emphasized in previous studies, especially in terms of the fundamental understanding of the effect of evacuation behavior upon information strategies and vice versa. An understanding of evacuee behavior in terms of their response to the changing environment and control strategies by EMAs throughout the evacuation process is critical for both the planning and operational contexts. For operational control, this effectiveness depends significantly on the level of behavioral understanding of the demand-side problem. Methodological challenges arise from uncertainty and randomness in disaster dynamics and evacuees' decision process under extreme time pressure.

Some of the earliest studies on evacuation planning were motivated by the radiological emergency at the Three Mile Island in 1979 (Sheffi et al., 1982; Stern 1989). From the 1990s, many researchers have focused on addressing the evacuation problem motivated by several devastating hurricanes, which led to extreme damage in southeastern United States. After 9/11, there has been growing concern about the need to address mass evacuation under terrorist attacks. A number of models have been developed for the aforementioned studies on nuclear-site and hurricane related evacuation over the past decades. These models estimate the evacuation clearance time and identify potential bottlenecks under different scenarios. Alsnih and Stopher (2004) provide a review of these models and conclude that most of these models are static in the context of traffic flow modeling or estimate traffic flow dynamics through rather simplified macroscopic traffic flow models, where time-dependent demand is approximated by some prescriptive departure schedule.

In more recent studies, dynamic traffic assignment (DTA) approaches have been used to model the evacuation problem for large-scale networks under real-time conditions. Sbayti and Mahmassani (2006) proposed a bi-level framework of evacuation operation to jointly solve for the desired time-varying origin-destination pattern and traffic assignment using the system optimal (SO) DTA module of Dynasmart-P. Chiu et al. (2007) applied the concept of "super zone" to reduce multiple-destination SO-DTA to a single-destination problem. They derived the optimal destination-route-flow-departure scheme for no-notice evacuation utilizing a cell transmission model (CTM) based linear programming formulation proposed by Ziliaskopoulos (2000). DTA methods provide route guidance for the individual or system-wide objectives by assigning vehicular flows to the associated routes. However, a critical aspect for the successful deployment of DTA control strategies is the compliance of drivers to the recommended departure times and routes. Moreover, under the evacuation process, individuals may make decisions by assessing factors other than the provided travel time information; for example, the intensity and/or proximity of the threat or disaster.

To capture individuals' decision processes under evacuation scenarios, it is important to address the related issues and characteristics of driver behavior. Prashker and Bekhor (2004) extensively reviewed different models of driver's route choice behavior in traffic assignment problems. Driver's behavior in an evacuation network, however, may be much different from that in a regular network, as evacuees face time pressure and an existential threat from extreme events. Current literature on choice behavior under both types of evacuation is limited. For short-notice evacuation, there has been research on modeling demand generation associated with hurricane evacuation through an aggregated representation using logistic regression and neural network models (Wilmot and Mei, 2004), sequential logit model (Fu and Wilmot, 2004) and survival analysis (Fu and Wilmot, 2006). These models were estimated and tested using a data set of evacuation participation collected in southwestern Louisiana following Hurricane Andrew in 1992. Chiu and Mirchandani (2008) proposed an online information routing system considering behavioral feedback for a flood scenario, where route choice behavior was modeled using a C-logit model and calibrated using the stated preference approach. For no-notice evacuation, to the best of our knowledge, behavior issues have not been empirically and quantitatively studied in the literature. To address the inadequacy, this research aims to propose a model that: (i) investigates zonal behavior in considering practical implementation and data availability under no-notice evacuation operations at an aggregate level, and (ii) highlights the importance of understanding behavioral issues/phenomena under evacuation and provides a platform for designing behavior-robust information strategies for more effective dynamic routing.

The next chapter describes the problem characteristics of behavior under no-notice mass evacuation and defines the scope of the problem. Chapter 3 provides an introduction of the methodology adopted for modeling the problem. Chapter 4 presents the model formulation to capture influential factors for evacuation behavior. Chapter 5 examines the robustness of the proposed behavior model using a numerical experiment, followed by concluding comments in Chapter 6.

CHAPTER 2. PROBLEM DESCRIPTION

The main focus of this study is to understand how people respond to information provided as part of system-wide control strategies in evacuation environments. Due to practical issues related to data availability, the study focuses on aggregate behavior in the evacuation network in that the aggregate behavior of individuals in a traffic analysis zone (TAZ) is addressed as zonal behavior since it is difficult to obtain disaggregate data under real-time evacuation operations. Despite being modeled at an aggregate level, an understanding of individual behavior provides insights of problem characteristics which are critical for modeling the problem.

2.1 System components in an evacuation problem

Overall, the operation of mass evacuation starts from the issuance of a disaster warning and then an evacuation notice. Under some circumstances, such as no-notice disasters, the issuance of disaster warning and evacuation notice might be simultaneous. The issuance of evacuation notice also involves the definition of the evacuation area, the sequential order in which zones are evacuated (if phased evacuation is considered), and the provision of shelters. The operation further includes traffic routing and management strategies, aid to people who need special care (such as the elderly, injured, disabled, etc.), organizing evacuation fleets, and related emergency services. When the evacuation problem is viewed in terms of the traffic flow patterns, it presents a system which needs to be scrutinized from three facets: disaster, demand and supply.

Disaster

In the evacuation context, a disaster is characterized by how it impacts the evacuation areas. The key disaster attributes in an evacuation problem are the disaster intensity, spatiotemporal pattern, destruction to the network, and the level of predictability.

- Intensity: The intensity of a disaster implies its destructive strength and risk level. It relates to the potential loss of life and property in the affected areas. The intensity of a disaster can be represented using objective measures, such as the wind speed of hurricanes and the magnitude of earthquakes on the Richter scale. However, such measures may not be meaningful to the people who are not familiar with the disaster. And for some disasters, for example, chemical spills, there may not be an acknowledged measure to describe the intensity of disasters. Instead, the general public is more likely to perceive disasters qualitatively in terms of the severity of damage and/or casualties. In addition, there is no universal measure of intensity that can be applied to different disaster types. Hence, different disaster types may lead to different behavioral responses among the public (Nozawa et al., 2008).
- Spatiotemporal pattern: Most disasters are time-varying in coverage and/or have certain trajectories (including the location of occurrence), and manifest as spatiotemporal patterns in terms of how they evolve over time and impact the areas. This characteristic is important to define the evacuation areas and to determine the directions in which to evacuate the affected people. The spatiotemporal pattern provides information on the distances between the disaster frontier and the locations of the areas threatened by it. It enables projecting the level of danger to these areas.
- Destruction to the network: To the system managers concerned with traffic management, disasters may reduce roadway capacity or cause link failure through physical destruction or obstruction (e.g. earthquake, inundation), limited visibility (e.g. smoke, heavy rain) or other risk factors (e.g. gale). Hence, the link conditions in the evacuation network must be monitored throughout the operational horizon. Doing so can also indicate opportunities for capacity recovery if/when the situation

permits. Further, the relevant information must also be disseminated to the public as part of the information provision strategies.

- Level of predictability: The level of predictability refers to the degree to which the above-mentioned characteristics of disasters can be estimated in advance of an event. While uncertainty is generally embedded in disaster dynamics, some disasters are more predictable than others. For example, it may be possible to capture the characteristics of a hurricane using meteorological techniques before its landfall, while it is still considered difficult to predict the occurrence of a devastating earthquake using state-of-the-art techniques. Additionally, the quality of prediction may also vary. Thereby, the predictability of a disaster directly affects the ability to issue a timely warning and/or evacuation notice.

For an evacuation problem, starting from the issuance of the evacuation notice, it is assumed that the dynamics of the disaster characteristics are available through other sources as inputs to the problem.

Demand-side components

Demand-side components refer to the individuals to be evacuated from the endangered areas upon the issuance of an evacuation notice. They manifest as the surging demand within a short period based on how individuals respond to environmental factors (from the disaster, supply-side and even the interactions among demand-side). It determines the traffic pattern in the evacuation network. The issue also highlights the significant complexity to the problem arising from the potential behavioral heterogeneity across individuals.

Although a range of environmental factors may be considered by individuals under different evacuation situations, a previous study (Mawson, 2005) suggests that the dominant ones include perceived risk and seeking social attachment. Social attachment refers to familiar persons or places. In the evacuation context, the behavior of seeking social attachment is revealed in terms of concerns about household members. It has been observed that parents seek to go to their children’s locations first before leaving the evacuation areas (Stern, 1989). Additionally, researchers have observed herding behavior from building evacuation and pedestrian flows (Mawson, 2005; Song 2005). Such a phenomenon is also a manifestation of social attachment in that people's decisions affect each other. Most people tend to mimic others' actions, due to the limited time for deliberation. In the current study, which considers evacuation operations from the perspective of traffic management, the information provided and/or recommendations may also affect individuals' assessment of alternatives, and therefore, decision-making.

The effects of these environmental factors depend on how each individual perceives and interprets the situation. Such perception and interpretation involve subjectivity based on personal attributes. Herein, preparedness is indicated as a central feature for individuals' behavior under emergency (Tierney et al., 2001). It generally describes a behavioral basis of the public toward the overall process of disaster management, which broadly includes disaster prevention, relief, recovery, etc. In terms of the evacuation operation, an awareness of the hazard can influence the underlying behavior of an individual. Each individual's awareness of the hazard is related to: (i) his/her prior experience with disasters and/or evacuations, (ii) education and training that he/she has received related to the disaster preparedness, and (iii) influence of information or news reports about disasters (Lindell and Prater, 2000). Individuals who are more aware of hazards are likely to be more vigilant and familiar with the evacuation operation, and hence, can more properly respond. Additionally, in the context of evacuation network management under information provision, individuals' confidence in information and familiarity with the network are potential factors, as is an individual's socioeconomic background.

Supply-side components

Supply-side consists of the components that physically provide capacity to evacuate the public from the endangered areas and enable the management to facilitate long-term or short-term evacuation operations. The details are discussed in terms of the transportation system, evacuation plan and operational strategy:

- Transportation system: It broadly includes all kinds of modes that can be utilized to move the public out of the endangered areas under a disaster situation. This study focuses on the vehicular traffic network, in which the configuration/geometrics of the roadway system determines the capacity of the evacuation network.
- Evacuation plan: The evacuation plan is the long-term management strategy determined by analyzing likely events, which: (i) establishes pre-disaster schemes of traffic flow patterns that enable the fastest evacuation, (ii) identifies the potential bottlenecks and vulnerable infrastructure in the roadway system from the above schemes, and (iii) determines corresponding strategies to strengthen the identified critical bottlenecks of the network. Other than the roadway system, the evacuation plan can also include the operation of public transit and other evacuation fleets. Public transit may not be able to operate normally, and therefore a plan for extreme events is needed to serve low-mobility demand. For some institutions, such as schools and hospitals, pre-planned evacuation fleets can carry their members (students and patients) to places of safety. Such an arrangement can reduce the complexity of evacuation traffic, incurred by the aforementioned behavior of seeking social attachment in which evacuees rush to their family members before moving to designated safe places.
- Operational strategy: In contrast to the evacuation plan, operational strategies are implemented to achieve the desired traffic flow patterns as well as to account for the actual conditions unfolding on a real-time basis. Contra-flow lanes and signal control modification are commonly adopted strategies to increase the throughput in the outbound directions. Information control strategies yield the same purpose from the perspective of demand management. Information provided by EMAs can be descriptive content about disaster and traffic conditions or prescriptive statements, which indicate when to depart, where to go and which route to take with different levels of mandate. The information strategies can be delivered through several kinds of channels; some are available for customized information, like on-board communications or cell phones, while most are accessible to the general public or to

the individuals at a certain location, like TV, broadcast and variable message signs (VMS). Hence, coordination between different dissemination channels is required for information consistency.

2.2 Problem characteristics

The characteristics of the evacuation problem are determined by the system components introduced in the last sub-section. The evacuation areas are identified according to the disaster's trajectory, followed by the estimation of the demand from the evacuation areas and the corresponding vehicular network, and manifest in terms of the dynamics of evolution of system components. However, further discussion is needed to model behavior under no-notice mass evacuation.

No-notice evacuation versus short-notice evacuation

No-notice and short-notice evacuations differ primarily in terms of the disaster's predictability of occurrence. While a no-notice evacuation needs to start immediately after the occurrence of such a disaster, the pre-evacuation warnings of short-notice disasters allow a lead-time (24-72 hours) before the disasters strikes. Such a lead-time represents the essential difference between no-notice and short-notice evacuations. From a demand-side perspective, with the lead-time, individuals may be able to better judge the severity of disaster impacts, analyze possible courses of actions, and then make decisions. By contrast, under no-notice disasters, individuals need to respond to the changing environment very quickly under a higher level of time pressure.

Empirical studies (Kang et al., 2007) suggest that with a lead-time most individuals would go back to their house, get together with household members, and consider securing their houses or protecting property. However, this is impractical under no-notice evacuation, especially when the disaster is very severe and tremendous threat is perceived. Under such situations, individuals may just intend to get out of the impacted areas as soon as possible, but not deliberate on their trip planning (for example, to select a shelter in terms of houses of relatives/friends, hotels/motels or public shelters as trip destinations). Moreover, the circumstances make it less likely for individuals to make precise plans. Instead, people may tend to adopt some simple rules with approximate judgment, under time pressure due to the emergency.

Evacuation objectives

Depending on the disaster situation, different objectives may be adopted for an evacuation operation, including: (i) to minimize network clearance time or to clear the network by some specified (feasible) time, (ii) to maximize the number of people exiting the evacuation areas, and (iii) to minimize the number of casualties or the exposure to the affected area or environment. Though different objectives may exist, their realization would involve the explicit consideration of congestion mitigation strategies (the operational strategies mentioned in the previous sub-section) that improve network efficiency to serve the sudden demand.

Interactions between demand and supply

As the disaster represents an uncontrollable environmental factor, individual behavior and the implementation of operational strategies depend on the how demand and supply respond to the actions by each side. As indicated in the last sub-section, individuals make decisions in response to the evolving environment, including supply-side factors such as the estimated traffic conditions and the information provided (or recommendation). However, the dynamics of traffic flow pattern representing the collective outcome of individuals' travel behavior are a complex factor affecting the determination of traffic management (supply-side) strategies. This interplay leads to the evacuation operation being an adaptive process. A model may be unrealistic if it does not carefully capture the processes associated with these interactions.

Individuals' perspectives versus system managers' perspectives

In addition to the interactions between demand and supply, another issue arises from the discrepancy in the problem interpretation from different perspectives. From individuals' perspective, each individual perceives the environment and responds based on his/her own behavioral considerations, which can be different across the population. However, from a system manager's perspective, it is difficult to track each individual's behavior. Instead, it may be possible to observe the dynamics of demand-side components at an aggregate level, for example, through the traffic counts on certain links. Further, while it may be desirable to have personalized information guidance for each individual, for practical deployment it is more realistic to approach the problem within a macroscopic framework due to data availability considerations, whereby individual behavior is aggregated at the level of TAZs.

Accordingly, the heterogeneity across the individuals is an issue to be addressed. Further, the boundaries of TAZs need to be pre-planned based on data availability, population size, and network configuration. In this context, the TAZs used for standard transportation planning may be good candidates, with some potential adjustments.

2.3 Research scope and framework

By focusing on the integration of demand-supply management with information guidance as control strategies for evacuation operations, Figure 2.1 conceptually shows the framework for this study, where the behavior-based information control system incorporates individuals' likely responses when determining information strategies using the control model. In the control system, information strategies are derived based on: (i) the observed evacuation flow pattern via a monitoring system, (ii) disaster information obtained from the relevant external sources, and (iii) the estimated response of the affected population. The iterative computation between the behavior model and the control model is processed to generate control output, which directs traffic flows to the controller-desired pattern. Compared to conventional evacuation models, which assume full compliance of individuals to the optimal assignment, the proposed procedure better represents the real-world behavior while capturing the interplay between demand and supply. This study focuses on the behavior model (the gray box located in Figure 2.1) which aims to predict the aggregate behavior of TAZs based on the evolving conditions.

Figure 2.2 further illustrates the research scope related to the demand management under no-notice evacuation. The total evacuation demand includes: (i) the affected population that has not yet joined the vehicular traffic, and (ii) the background traffic in each TAZ under the disaster. Two models are proposed to address the behavioral aspects of evacuation: the model for evacuation participation decision and the model for evacuation route choice. The first predicts the decisions of individuals who have not yet joined the evacuating traffic in each zone. The second estimates the distribution of vehicular flows to the set of the evacuation paths, thereby describing the traffic flow pattern in the evacuation network. Hence, these two behavior models capture the aggregate emergent behavior of the people in the TAZ under the information provision strategies and the unfolding environment they perceive.

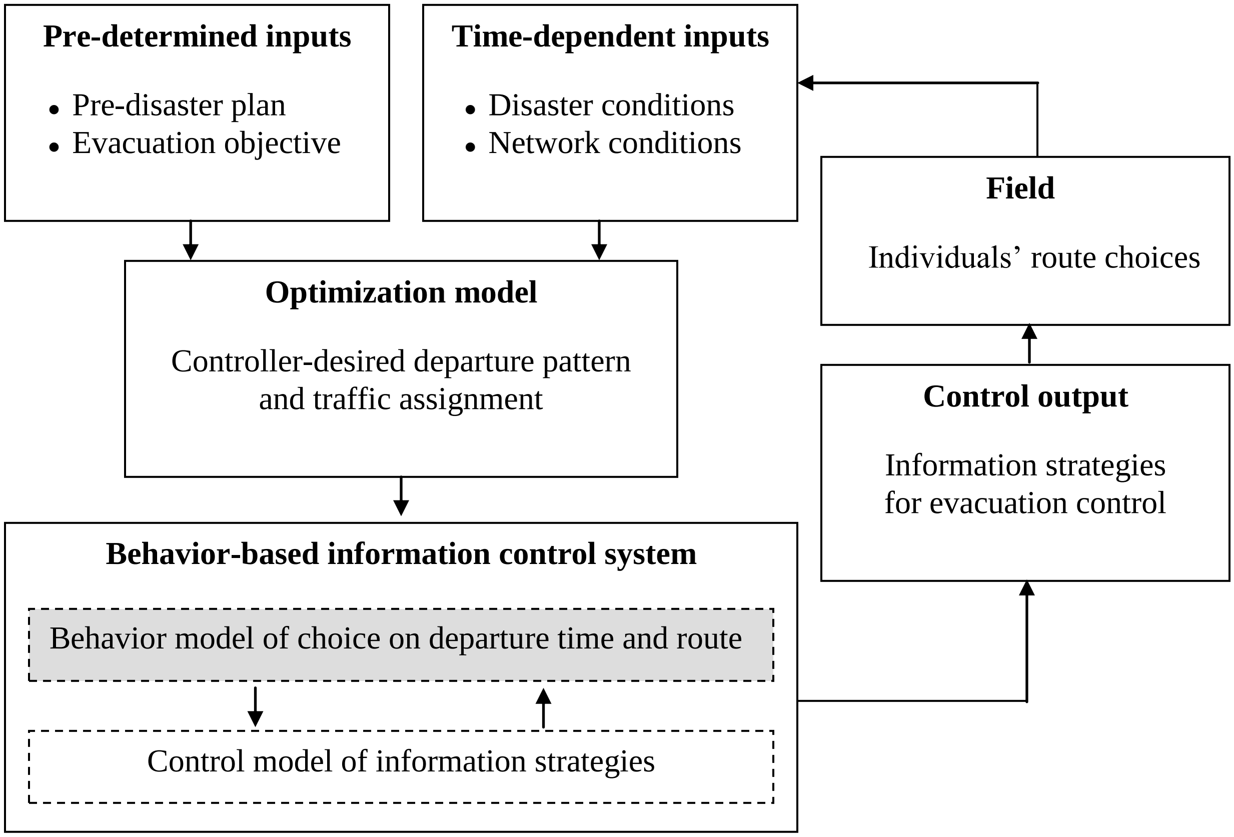


Figure 2.1. Conceptual framework of information control for evacuation operations

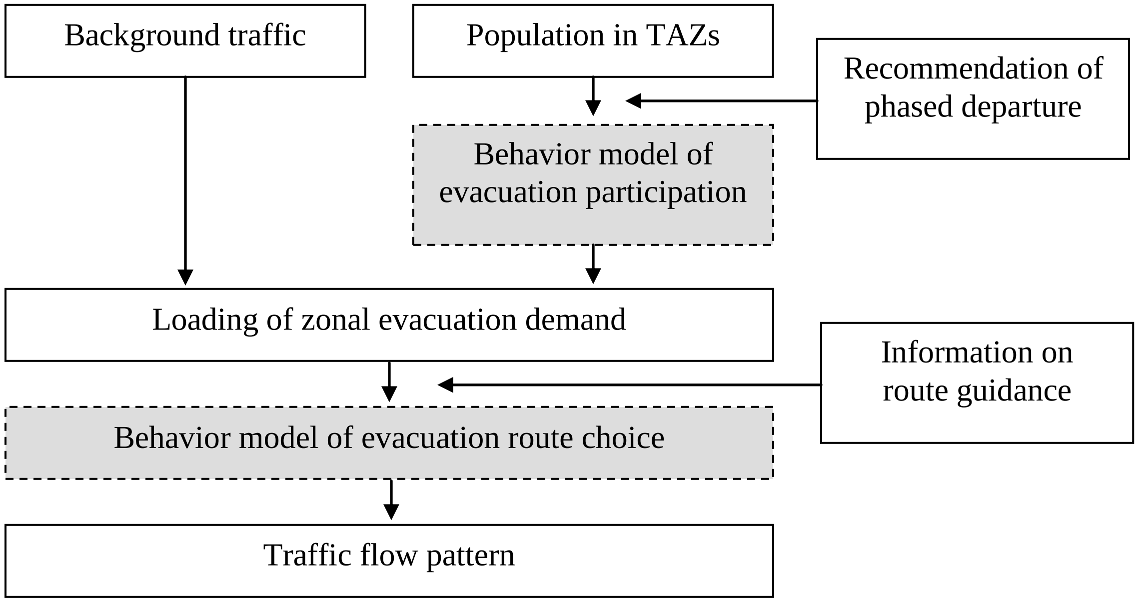


Figure 2.2. Flowchart of the aggregate behavior model in a no-notice evacuation

CHAPTER 3. METHODOLOGY

The modeling of the behavior of evacuation participation and route choice at an aggregate level, based on the problem characteristics discussed in the previous chapter, must accommodate the following considerations:

(i) Key factors, such as perception of risk, that involve subjective interpretation rather than objective assessments and/or observable measurements.

(ii) During the evacuation process, the information about disaster, traffic conditions and other important issues that may entail linguistic description; for example, "the disaster is severe" or "may be seriously congested", rather than numerical measurements.

(iii) At an aggregate level, the perception of environmental factors may vary across individuals in a TAZ based on personal attributes, which highlights the issue of heterogeneity for model consistency.

The proposed model adopts discrete choice theory, which is commonly employed in modeling choice behavior. However, to address the above issues, fuzzy set theory is further incorporated into the model within the structure of the mixed logit model. The methodological justification is detailed in the following sub-sections.

3.1 Randomness and fuzziness

While choice behavior under uncertainty is embedded with randomness, the issues (i) and (ii) induce the issue of fuzziness to the problem, especially under the threat from disasters and time pressure issues. As discussed in Chapter 2, though precise measurements on the intensity of the disaster may be available, they may not mean a lot to an individual who is not familiar with the disaster. Instead, other information, such as reported casualties or damage, can more directly enable his/her perception, which is more a qualitative or subjective interpretation than quantitative evaluation.

Traditionally, probabilistic choice model is adopted in discrete choice theory. However, compared to probabilistic modeling approaches that capture behavior randomness through well-defined probabilistic distributions over measurements or categories, fuzzy set theory can better address the judgments associated with linguistic expressions or qualitative data. For example, qualitative data are generally modeled using categorical variables to indicate the states of the attribute with clear boundaries in probabilistic approaches. But, an individual's perception of risk may lack a clear boundary between "risky" and "not risky". In contrast to the conventional Boolean logic with values just for "true" and "false", fuzzy set theory introduces membership functions that allow partial belonging of a variable by assigning it a value between 0 and 1. The value, termed as fuzzy value, indicates the degree of evidence that the variable belongs to a set of an attribute's state; for example, how much degree the environment or certain information about a disaster is perceived by an individual as "risky" or "not risky". The fuzzy logic approach provides another advantage of modeling such fuzzy variables by using if-then rules for evacuation situations. Under evacuation operations, individuals are more likely to make decisions based on some simple and straightforward rules, because the time to process information and assess alternatives is limited. Therefore, a fuzzy rule-based framework can better capture evacuation behavior. To obtain values for such fuzzy variables, Peeta and Yu (2002) provided a comprehensive review and description to quantify linguistic expressions or qualitative data. Further, a hybrid choice model proposed by Peeta and Yu (2004) is adopted to accommodate both fuzzy variables and probabilistic variables simultaneously if both are involved.

3.2 Mixed logit model

In the proposed aggregate model, each TAZ is treated as an individual. That is, the probability of selecting a certain alternative as aggregate behavior for a TAZ is considered as the proportion of the individuals in the TAZ who select the alternative. To address the issue (iii) above, in most of discrete choice models, heterogeneity among population is represented by including socioeconomic or other personal attributes as variables in utility functions. But when such individual-level data are unavailable, a mixed logit model provides a convenient structure to accommodate heterogeneity in an aggregate discrete choice model. A mixed logit model allows random parameters and is defined as any model whose choice probabilities for decision maker *n* to choose alternative *i* can be expressed in the form (Train, 2003):

$$P_{ni} = \int \left(\frac{e^{V_{ni}(\beta)}}{\sum_j e^{V_{nj}(\beta)}} \right) f(\beta \mid \phi) d\beta \tag{1}$$

where $\frac{e^{V_{ni}(\beta)}}{\sum_j e^{V_{nj}(\beta)}}$ is the choice probability evaluated at parameters β using a standard logit model, and $V_{ni}(\beta)$ is the systematic component of the utility function of alternative *i* to decision maker *n*.

In contrast to the standard logit model, β does not consist of constant values, but is distributed over a certain attribute ϕ, where $f(\beta \mid \phi)$ is the density function, also termed as mixing distribution. With this structure, the mixed logit probability can be viewed as a weighted average of the regular logit formula evaluated at different β, and the weights are given by the density function. The integration procedure can also be treated as the aggregation of individual decisions to a zonal level.

The parameters β can be interpreted as a decision maker's tastes on corresponding variables. A higher absolute value of a parameter implies higher importance of the corresponding variable to the decision maker. In a standard logit model, the results of estimation indicate average effects of the variables to the sampled individuals, while the structure of a mixed logit model enables the estimation with β (tastes) varying across individuals with different values of attribute ϕ, which can be treated as heterogeneity at a disaggregate level. In addition, unlike a probit model that also allows random parameters but is limited to normal distributions, the mixing distribution of a mixed logit model can be in a variety of forms, both discrete and continuous.

Besides allowing for random taste variation, a mixed logit model represents the most generalized structure of overcoming the problems of correlation in unobserved factors and restricted substitution patterns, compared to a standard logit model or other extended models from the logit family. The issue of correlation generally exists in multi-choice problems. For modeling route choice behavior, the correlation between routes, which is assumed non-existent in regular logit models, could be significant in producing estimation bias if not accounted for. For choosing evacuation routes, such correlation might result from common links between routes, the same level of perceived risk or familiarity across different routes, and other unobserved factors. The adoption of a mixed logit model can avoid this dependency problem, while retaining the computational simplicity of the logit form.

CHAPTER 4. MODEL SPECIFICATION

For an efficient evacuation operation, this study assumes that there is a pre-disaster plan that requires certain institutions, such as schools and hospitals, to take the responsibility of evacuating their members (students and patients) to places of safety by pre-organized evacuation fleets. For operational clarity, the plan must be known to the families of children and/or other members in the associated institutions, and should not allow separate pick ups on the institutional premises. Otherwise, the traffic pattern induced from such trips to pick up family members can be complex and reduce operational control by the system operators. In this study, it is assumed that such "pick-up" trips are eliminated by the pre-disaster plan, and that the concern for family members' safety is not an attribute of the choice model.

Individual behavior under the context of evacuation problem can be viewed as a hierarchical one. First, an individual makes the decision whether to evacuate at a certain time stage or not (that is, to postpone the decision to evacuate to a future time stage). The decision at this level primarily depends on:

(i) perceived risk, which is derived from the information about the disaster.

(ii) recommendation or order to evacuate (or not to evacuate) at the current time stage from the EMA.

(iii) herding behavior (or peer effect), which is observed in that people tend to follow the decisions of others.

(iv) state dependence, which is due to non-evacuation decisions in previous time stages, from the perspective of evacuation operation. That is, if an individual does not evacuate in the last time stage, his/her decision to evacuate or not in the current time stage will be affected by his/her previous decision. It is also assumed that as the number of non-evacuation decisions increase, there is more pressure on an individual to make a decision to evacuate in this time stage.

In this study, we assume that disaster information (related to (i)) and recommendation (related to (ii)) are available to each individual through various channels such as TV, radio broadcast, the Internet, etc. For all individuals in a certain TAZ, the information and recommendation from different channels should be consistent with each other. For herding behavior (as mentioned in (iii)) and state dependence (identified in (iv)), proxy variables are employed to capture their aggregate effects. In the proposed model, the number of people who have already participated in evacuation is the proxy variable for herding behavior. Also, the number of time stages since receiving the evacuation order (which implies the number of non-evacuation decisions made by the individuals who have not evacuated until this time stage) is the proxy variable for state dependence.

If an individual decides to evacuate (representing the first level decision), then he/she is considered as making a decision to enter the evacuation network. At this point, the individual needs to make a decision at the second level, that is, which route to evacuate on. The problem at this level is somewhat similar to the route choice under normal traffic, where traffic conditions typically represent the primary focus. However, under no-notice evacuation, we further assume that people first tend to seek a safe area as soon as possible, and then travel to their final destinations (home, or to get together with family members) later. Accordingly, in our problem modeling, an individual does not deliberate on the destination of the evacuation trip, but selects a route from among several routes which lead him/her to the nearest safe places. In this context, the key variables influencing the decision at the second level include:

(i) estimated travel time from the information available on traffic conditions.

(ii) perceived risk on the route based on the disaster's potential impacts or the possibility of link failure.

(iii) recommendation or guidance from the EMA about the route to take.

(iv) freeway bias, which has been observed from previous stated preference surveys (Chiu and Mirchandani, 2008) that indicate that the route through freeway is considered more reliable and preferred, though the reported travel time on the route is more than that on other arterials. Freeway bias is defined as the proportion of the length on freeway to the total length of the route.

Evacuation Participation (Decision) Model

This aggregate binary choice model at the level of a TAZ seeks to predict the evacuation decision (to evacuate (1) or not (0)) of the individuals who have not evacuated in a certain zone. The output of the model is the proportions of the individuals who decide to evacuate (and not to evacuate). A discrete choice model is used with "not to evacuate" as the base alternative for a TAZ *n* at a time stage *t* (in the following expression, for notational simplicity we omit the subscript *t* in the utility functions and variables). The systematic utility of the alternative, "to evacuate", is:

$$V_n = \alpha_n + \beta_1(\phi)R_n + \beta_2(\phi)M_n + \beta_3(\phi)H_n + \beta_4(\phi)S_n \qquad (2)$$

where α_n is the alternative specific constant, and $\beta_i(\phi)$ is the random coefficient of the corresponding variable whose values are conditioned on the distribution of some underlying attribute of the population, ϕ. R_n, M_n and H_n are the fuzzy values to represent the perceived risk, the effect of recommendation from the EMA, and the effect from other people's actions, respectively. For the zone n, S_n is the number of time stages since receiving the evacuation order. Using the structure of the mixed logit model, the estimation result determines the probabilities that the individuals in TAZ *n* decide to evacuate, P_n. Aggregating, the number of evacuees loaded to the network at certain time stage is the number of people who have not evacuated multiplied by P_n. The values of

R_n , M_n , H_n are determined using the corresponding IF-THEN rules in Table 4.1, and the approach provided by Peeta and Yu (2002) to quantify the qualitative data.

Evacuation Route Choice Model

This model determines the route choice decisions of individuals in the vehicular traffic in the evacuation area, including en-route vehicles and those who just made the decision to evacuate and need to choose an evacuation route from the zone where they are located. The model output is the proportion of traffic in a certain TAZ assigned to routes to evacuate. Only likely routes to the nearest locations of safety are considered as the set of alternatives for the vehicles in a certain TAZ. The systematic utilities are represented as follows, except that no alternative-specific constant is specified for one alternative:

$$V_{nk} = \delta_{nk} + \gamma_1(\varphi)T_{nk} + \gamma_2(\varphi)L_{nk} + \gamma_4(\varphi)F_{nk} + \gamma_4(\varphi)G_{nk} \tag{3}$$

Akin to the evacuation participation model, δ_{nk} is the alternative specific constant, and $\gamma_j(\varphi)$ is the random coefficient of the corresponding variable, which is conditioned on the distribution φ of the attribute of the heterogeneous vehicular flows in the zone. T_{nk} , L_{nk} , F_{nk} and G_{nk} are fuzzy variables, which represent estimated travel time and/or delay on route *k*, perceived risk on the links of route *k*, freeway bias, and the effect from the recommendation or guidance that suggests drivers to take route *k*. As in the evacuation participation model, the corresponding IF-THEN rules in Table 4.1. are employed to determine the values of T_{nk} , L_{nk} , F_{nk} and G_{nk} .

Table 4.1. Fuzzy IF-THEN rules

Attribute	LHS	RHS
Evacuation Participation (Decision) Model		
Perceived risk to TAZ	If minor damage is reported If some damage is reported If serious damage is reported	He/she will perceive less risk He/she will perceive some risk He/she will perceive high risk
	If the TAZ is reported not to be struck If the TAZ is reported likely to be struck If the TAZ is reported very likely to be struck	He/she will perceive less risk He/she will perceive some risk He/she will perceive high risk
	If the disaster's frontier is distant from the route If the disaster's frontier is close to the route	He/she will perceive less risk He/she will perceive high risk
Recommendation to evacuate	If the recommendation to stay is mandatory If the recommendation to stay is voluntary If no specific recommendation If the recommendation to evacuate is voluntary If the recommendation to evacuate is mandatory	He/she will stay He/she will probably stay He/she will be neutral He/she will probably evacuate He/she will evacuate
Herding behavior	If most individuals have not evacuated If about half of the individuals have evacuated If most of the individuals have evacuated	He/she will stay He/she will be neutral He/she will evacuate
Evacuation Route Choice Model		
Estimated delay on route	If the route is reported as having no congestion If the route is reported congested If the route is reported seriously congested	He/she will expect no delay He/she will expect some delay He/she will expect serious delay
Perceived risk to route	If the disaster's frontier is distant from the route If the disaster's frontier is close to the route	He/she will perceive low risk on the route He/she will perceive high risk on the route
Freeway bias	If most links on the route are freeway links If some of the links of the route are freeway links If few of the links on the route are freeway links	He/she will prefer the route He/she will be neutral He/she will not prefer the route
Recommendation on evacuation route	If the recommendation not to take the route is mandatory If the recommendation not to take the route is voluntary If no specific recommendation If the recommendation to take the route is mandatory If the recommendation to take the route is voluntary	He/she will not take the route He/she will probably not take the route He/she will be neutral He/she will probably take the route He/she will take the route

CHAPTER 5. NUMERICAL EXPERIMENTS

5.1 Experimental setup

In the absence of field data for no-notice evacuation, simulation experiments are conducted using the scenario of a terrorist attack in a populated area. The proposed choice models are tested with the data from the simulation experiments to analyze if the models can robustly interpret the observed traffic in an aggregate context from a behavioral perspective. The simulation is performed using a mesoscopic vehicular network traffic simulator, DYNASMART. The details of experimental setup are described hereafter.

Study Network

The simulation experiments are conducted using the Indianapolis downtown area network to illustrate the prediction capability of the proposed models. The study (evacuation) network is shown as Figure 5.1 (the circled area on the left-hand side). The right-hand side of Figure 5.1 is the simplified network for simulation, which has 298 nodes, 972 links, and 24 TAZs. It is assumed that a terrorist attack occurs in the Indianapolis downtown area as indicated in the figure. A 90-min evacuation operation is conducted with 10 minutes for each of the 9 time stages, and with 24,000 vehicles to be evacuated and 6,000 vehicles as background traffic.

Data Generation: Individual Behavior

The purpose of the simulation experiments is to test the ability of the proposed models to capture individual behavior under available data. The data are generated using assumptions on the choice behavior structure of individuals related to evacuation participation and route choice. It is important to note that the assumed behavior structure is not known to the proposed models, while the input to the models are only the observable and controllable data available to the system managers; for example, link flow volume, and disaster and traffic information.

Individuals' behavior is assumed to be based on the variables discussed in the previous chapter: perceived risk, estimated travel time, peer effect, freeway bias, and recommendation. As these are fuzzy variables, values between 0 and 1 are assigned to them. However, to incorporate the heterogeneity across the population, each individual is assigned a value for each variable based on a range, which implies that individuals have different interpretation and/or perception under similar situations.

In terms of the decision-making process to generate synthetic behavior data, it is assumed that each individual makes decisions using a dominant variable with some pre-defined criterion at the first level. If decisions cannot be determined accordingly, the utility of the alternative as a linear combination of all the considered variables will then be compared to generate a decision at the second level. For the evacuation participation decision, perceived risk, peer effect and the effect of recommendation by EMA are considered the dominant variables for different classes of individuals. Then, for instance, in the class where perceived risk is the dominant variable, individuals' choices are generated by comparing the assigned value of perceived risk with the decision criterion. In the experiment, we set an indifference band between 0.25 and 0.75. If the value of perceived risk is higher than the threshold 0.75, the individual will choose to evacuate. If the value is less than 0.25, then the individual will not evacuate. If the value falls within the indifference band, then the computation of utility using all variables is needed to determine this individual's decision. The same procedure is applied for other classes, which consider peer effect or the effect of recommendation as the dominant variable. For the evacuation route choice, a similar two-level decision mechanism is used with estimated travel time, freeway bias and route guidance from EMA as the dominant variables for different behavioral classes. This mechanism of choice process highlights the possibility that individuals may use some simple rules with different key factors for decision-making. The behavioral difference accounts for the heterogeneity across the population due to some unobservable individual attributes in an aggregate context, such as socioeconomic background, past experience with disasters, confidence in disaster response plan, familiarity with the network, etc.

5.2 Analysis of results

For the study network, a scenario representing a terrorist attack is considered as shown in Figure 5.2. The models are tested for two selected TAZs, zone A and zone B, as indicated. One zone includes the location of the attack and the other is about half-way from the attack location to the safe areas.

The proposed models are analyzed in terms of their prediction capability of evacuation participation and route choice decisions in each time stage. The software Limdep 9.0 is employed to estimate the mixed logit models. The data were sub-divided for analysis and testing. 80% of the synthetically generated observations were used for model estimation, and the remaining 20% were used for model validation. The analysis determines the prediction error as shown in Figure 5.3, where the prediction error is calculated as the average of the difference between the predicted and observed choices across all alternatives. The results are shown for only some of the time stages for zone A, as most vehicles have evacuated or left the zone by the later time stages.

Figure 5.3 indicates that the prediction errors for both models range from between 15% to 30%. Another trend is that the prediction error tends to increase with the time stage. This may be due to the number of observations available for estimation. With the time stage moving forward, more individuals evacuate out of the zone, and the people who have not participated in evacuation are fewer. Hence, fewer observations for model estimation may degrade the prediction capability of the models.

Sensitivity Analysis

The simulation experiments further conduct sensitivity analyses related to demand levels and the amount of background traffic. Different demands levels and background traffic levels are considered as such conditions may arise with time-of-day for urban traffic. For instance, if the disaster occurs during the morning peak hours, commuters may not yet reach their work place; then, more vehicles form the background traffic. The network clearance time, defined as the time required from the start of the evacuation operation to the time that the last vehicle leaves the evacuation area, is used to analyze the sensitivity to demand and background traffic levels. The results are illustrated in Figure 5.4.

As shown in Figure 5.4, the network clearance time increases with the demand level as well as with the background traffic. While demand levels increase clearance time as expected, the effect of the background traffic can be explained in that more initial traffic volume in the network tends to create congestion at early stages of the evacuation operation itself and therefore induces longer time to clear the network.

Tables 5.1 and Table 5.2 show the model prediction capabilities relative to the demand and background traffic levels for zone A. For each demand level, it can be seen that the prediction error tends to increase with the time stage. The sensitivity analysis for background traffic ratio indicates that the prediction error of evacuation participation model increases with the background traffic ratio, while that of the route choice model shows the opposite trend. This is also related to the number of available observations, which suggests that the prediction capability of the models depend on the availability of data.

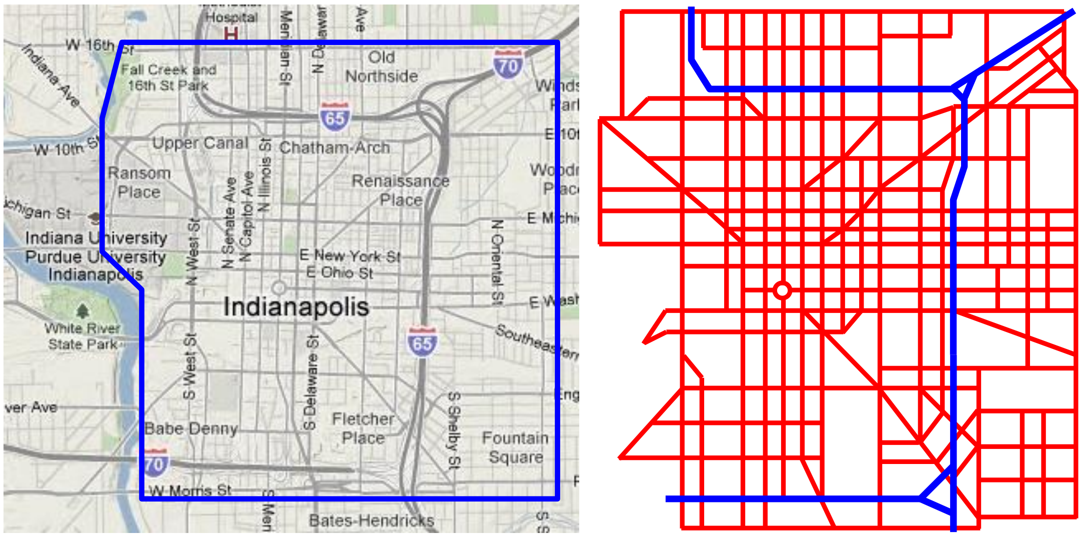


Figure 5.1. Study Network

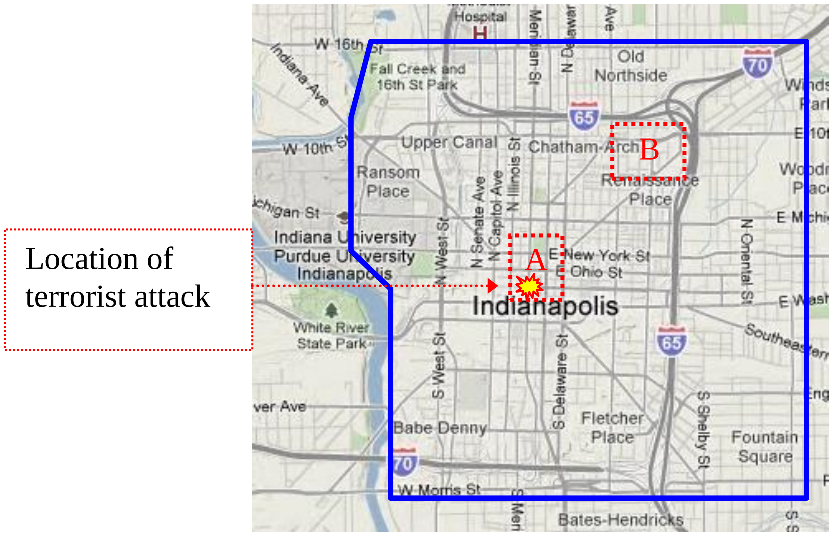


Figure 5.2. The location of terrorist attack and the TAZs for model testing

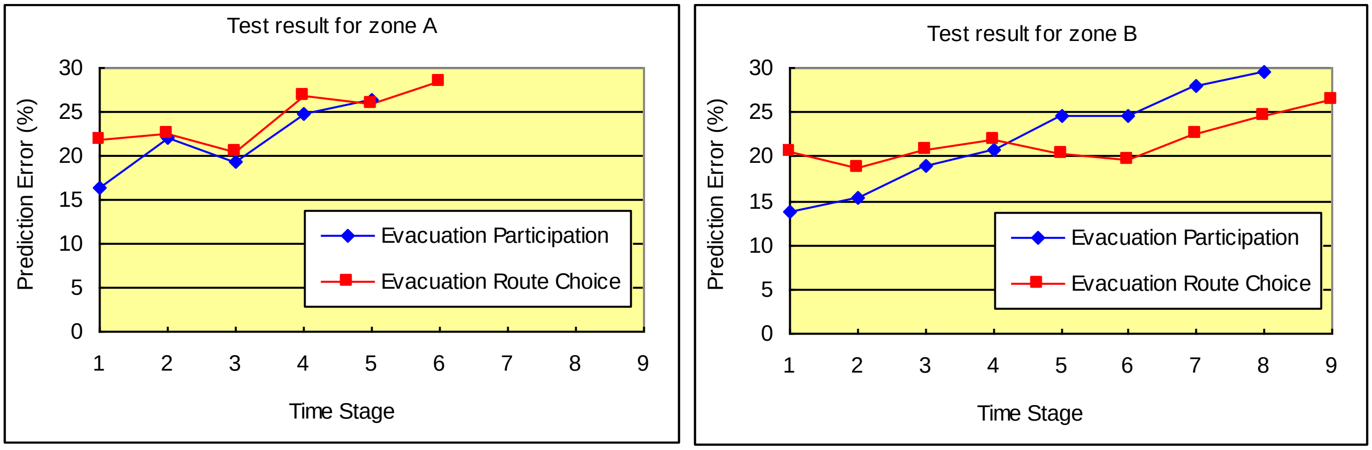
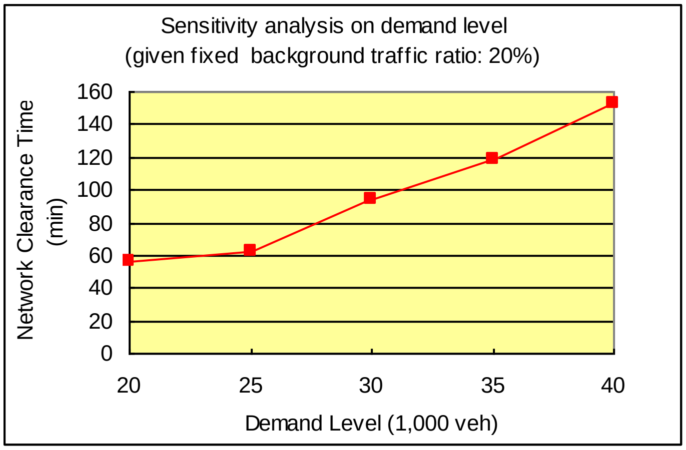


Figure 5.3. Prediction capability of the proposed models



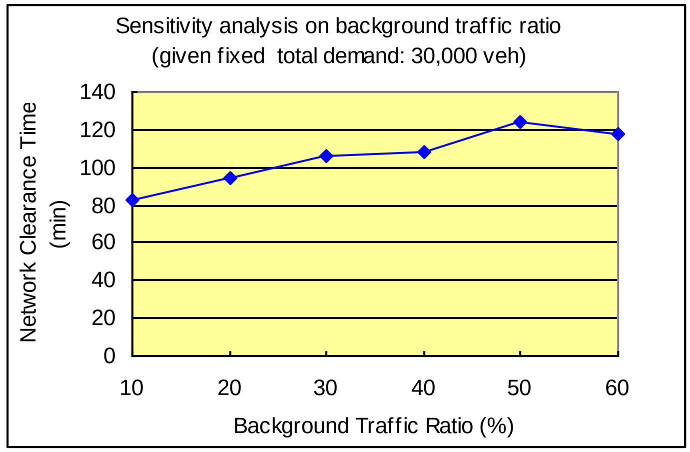


Figure 5.4. Sensitivity analysis of network clearance time with respect to demand level and background traffic ratio

Table 5.1. Sensitivity analysis (prediction error) for demand level

Demand Level	Model	Prediction Error (%) for Time Stages								
		1	2	3	4	5	6	7	8	9
20K	Participation	19.86	21.60	24.77	28.14	--	--	--	--	--
	Route	22.61	24.50	24.18	26.03	--	--	--	--	--
25K	Participation	17.25	22.43	23.62	27.32	27.11	--	--	--	--
	Route	22.54	23.65	23.81	25.16	26.67	27.58	--	--	--
30K	Participation	16.36	22.13	19.25	24.73	26.32	--	--	--	--
	Route	21.76	22.53	20.35	26.71	25.94	28.47	--	--	--
35K	Participation	16.27	18.71	19.40	21.33	21.15	23.84	26.80	29.07	--
	Route	18.54	19.23	20.72	22.00	22.86	24.53	26.64	27.43	28.06
40K	Participation	15.84	19.43	19.08	21.56	23.70	25.91	26.75	29.02	30.13
	Route	18.70	18.96	20.07	20.84	21.85	24.62	25.59	27.40	29.63

Table 5.2. Sensitivity analysis (prediction error) for background traffic ratio

Background Traffic Ratio	Model	Prediction Error (%) for Time Stages					
		1	2	3	4	5	6
10%	Participation	15.64	19.33	20.26	24.55	27.16	28.91
	Route	21.28	23.41	21.69	26.59	27.08	28.21
20%	Participation	16.36	22.13	19.25	24.73	26.32	--
	Route	21.76	22.53	20.35	26.71	25.94	28.47
30%	Participation	16.43	23.52	22.61	25.12	27.37	--
	Route	18.56	20.88	19.92	24.63	25.57	27.81
40%	Participation	18.24	21.58	22.09	23.56	26.78	--
	Route	18.32	19.07	20.85	22.36	27.33	28.40
50%	Participation	19.53	22.85	23.54	27.62	28.13	--
	Route	18.38	19.03	22.45	24.17	24.97	26.44
60%	Participation	21.27	24.89	24.77	27.41	--	--
	Route	16.76	20.34	23.57	25.12	27.14	--

CHAPTER 6. CONCLUSIONS

6.1 Summary

The long-term objective of this research is to address the mass evacuation problem from both demand and supply perspectives and capture the interactions between them, so as to develop an integrated management strategy for disaster-related mass evacuation. This study represents an intermediate step that focuses on the demand-side behavior aspects under no-notice evacuation, which has been addressed sparsely in the literature. The research contributions include:

1. This study reviews the characteristics of the mass evacuation problem from the viewpoints of disaster, demand and supply. Based on the problem characteristics, discrete choice models are developed by incorporating a fuzzy logic approach into the structure of mixed logit models to account for: (i) individuals' subjective interpretation and perception under time pressure, and (ii) the heterogeneity across the individuals in an aggregate manner.

2. Simulation experiments are conducted to test the prediction capability of the proposed models. The results indicate the ability of the models to interpret the evacuation behavior from observable variables at an aggregate level. The results also suggest that the number of observations for estimation is a key factor for the model prediction robustness.

6.2 Future research directions

In the context of real-world deployment, this study proposes aggregate behavior models based on data availability. However, the need for insights on human behavior under different kinds of disaster situations necessitates field surveys at a disaggregate (individual) level. Additionally, in the absence of field data, most studies on the modeling of mass evacuation rely on simulation, resulting in trade-offs in terms of realism. Hence, future research that develops robust behavior models at the individual level can be used to strengthen the behavior modeling components within a simulation framework. Based on the choice models proposed in this study, the next step in the research would be on constructing a behavior-based control model to develop more efficient evacuation strategies for EMAs to manage the system effectively from the supply side.

REFERENCES

Tuydes, H. and Ziliaskopoulos, A. (2006). Tabu-Based Heuristic Approach for Optimization of Network Evacuation Contraflow, Transportation Research Record, vol. 1964, pp. 157-168.

Kalafatas, G. and Peeta, S. (2007). An Exact Graph Structure for Dynamic Traffic Assignment: Formulation, Properties, and Computational Experience, Presented at 86th Annual Meeting of the Transportation Research Board, Washington, D.C., 2007.

Lindell, M. K. and Prater, C. S. (2007). Critical Behavioral Assumptions in Evacuation Time Estimate Analysis for Private Vehicles: Examples from Hurricane Research and Planning, Journal of Urban Planning and Development, vol. 133, no. 1, pp. 18–29.

Wolshon, B. (2002). Planning for the Evacuation of New Orleans, ITE Journal, vol. 72, no. 2, pp. 44–49.

Anon (2005). ITS to the Rescue. US Department of Transportation. http.//www.its.dot.gov/eto/eto rescue.htm.

Sheffi, Y., Mahmassani, H. S. and Powell, W. B. (1982). A Transportation Network Evacuation Model, Transportation Research Part A, vol. 16, no. 3, pp. 209–218.

Stern, E. (1989). Evacuation Intentions of Parents in an Urban Radiological Emergency, Urban Studies, vol. 26, pp. 191-198.

Alsnih, R. and Stopher, P. R. (2004). Review of Procedures Associated with Devising Emergency Evacuation Plans, Transportation Research Record, vol. 1865, pp. 89-79.

Sbayti, H. and Mahmassani, H. S. (2006). Optimal Scheduling of Evacuation Operations, Transportation Research Record, no. 1964, pp. 238–246.

Chiu, Y., Zheng, H., Villalobos, J. and Gautam, B. (2007). Modeling No-notice Mass Evacuation Using A Dynamic Traffic Flow Optimization Model, IIE Transactions, vol. 39, pp. 83–94

Ziliaskopoulos, A. K. (2000). A Linear Programming Model for the Single Destination System Optimum Dynamic Traffic Assignment Problem, Transportation Science, vol. 34, no.1, pp. 37–49.

Prashker, J. and Bekhor, S. (2004). Route Choice Models Used in the Stochastic User Equilibrium Problem: A Review, Transportation Reviews, vol. 24, no. 4, pp. 437–463.

Wilmot, C. G. and Mei, B. (2004). Comparison of Alternative Trip Generation Models for Hurricane Evacuation, Natural Hazards Review, vol.5, no. 4, pp. 170–178.

Fu, H. and Wilmot, C. G. (2004). Sequential Logit Dynamic Travel Demand Model for Hurricane Evacuation," Transportation Research Record, no. 1882, pp. 19–26.

Fu, H. and Wilmot, C. G. (2006). Survival Analysis–Based Dynamic Travel Demand Models for Hurricane Evacuation, Transportation Research Record, no. 1964, pp. 211–218.

Chiu, Y. and Mirchandani, P. B. (2008). Online Behavior-Robust Feedback Information Routing Strategy for Mass Evacuation, IEEE Transactions on ITS, vol. 9, no. 2, pp.264-274.

Nozawa, M., Watanabe, T., Katada, N., Minami, H. and Yamamoto, A. (2008). Residents' Awareness and Behaviour Regarding Typhoon Evacuation Advice in Hyogo Prefecture, Japan, International Nursing Review 55, pp. 20–26.

Kang, J. E., Lindell, M. K. and Prater C. S. (2007). Hurricane Evacuation Expectations and Actual Behavior in Hurricane Lili, Journal of Applied Social Psychology, vol. 37, no. 4, pp. 887–903.

Mawson, A. R. (2005). Understanding Mass Panic and Other Collective Responses to Threat and Disaster, Psychiatry, vol. 68, no. 2, pp. 95-113.

Tierney, K. J., Lindell, M. K. and Perry, R. W. (2001). Facing the Unexpected: Disaster Preparedness and Response in the United States, Joseph Henry Press.

Song, W., Xu, X., Wang, B. and Ni, S. (2006). Simulation of Evacuation Processes Using A Multi-Grid Model for Pedestrian Dynamics, Physica A, vol. 363, pp. 492-500.

Peeta, S. and Yu, J. W. (2002). Data-Consistent Fuzzy Approach for Online Driver Behavior under Information Provision, Transportation Research Record, no. 1803, pp. 76–86.

Peeta, S. and Yu, J. W. (2004). Adaptability of a Hybrid Route Choice Model to Incorporating Driver Behavior Dynamics under Information Provision, IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, vol. 34, no. 2, pp. 243-256.

Train, K. (2003). Discrete Choice Methods with Simulation, Cambridge University Press.