Analysis and Evaluation of Household Pick-up and Gathering Behavior in No-Notice Evacuations

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ABSTRACT

No-notice incidents occur with no advance notice of time and place. Family members may be separated when a no-notice incident strikes during the daytime. They may seek to gather the household members first and evacuate as a unit, and parents may head in the "wrong" direction to pick up their children from schools/daycare centers. Many previous studies have acknowledged that such behavior exists but few, if any, have examined it in-depth. Additionally, this behavior has rarely been integrated with transportation simulation models of evacuation conditions. As shown through this work, such omissions generate overly optimistic network performance. Acknowledging the behavior also leads to potential network improvements by moving dependents (people being picked up by other household members) to more accessible locations.

This study investigated no-notice evacuation household gathering behavior based on 315 interviews conducted in the Chicago metropolitan area, in which interviewees were asked about their evacuation and logistic decisions. The study analyzed household pick-up and gathering behavior from the interviews, developed models to represent the behavior, and integrated the household behavior models with network simulation modeling to examine the effects of household behaviors on network evacuation performance. Logistic regression models were built to predict the probability that parents retrieve children from school in normal and emergency situations. Gender, car availability, and travel distance (between parents and children) were the main influencing factors to determining child-chauffeuring travel behavior, where gender difference appeared to be most prominent. Women are more responsible for picking up children from school than men, and both women and men are more likely to pick up children under emergency conditions compared to a normal situation.

A complex model to integrating human behavior analysis and network assignment modeling was presented in this study. The model follows the traditional four step urban transportation planning process and 1) estimates household gathering chains in an evacuation using a discrete choice (Logit) model and sequences chains following the principle of "nearest first", 2) assigns directions of destinations ensuring the least travel time to safe zones from the last stop within the hot zones, 3) applies decision tree based mode choice models to determine the mode used for evacuation, and 4) uses a dynamic assignment method to assign time-varying demand to the network. The whole framework was tested in the Chicago metropolitan region for two hypothetical incidents, one causing a 5-mile evacuation radius and the other a 25-mile radius evacuation. The results showed that considering household gathering behavior will reduce proportions of evacuees who reach safe zones by a certain time period, while not necessarily deteriorating overall network traffic performance.

To facilitate the chain-based evacuations, a relocation model is proposed by moving carless dependents of facilities (such as schools and daycare centers) to more accessible locations for pickup; a linear integer program is presented to determine optimal sites. The optimization model uses estimated travel time obtained from a micro-simulation model and a procedure is presented to iterate between the two models (optimization and simulation). The methodology was applied to a sample network based on Chicago Heights, Illinois. The sample application involved four facilities with 780 dependents and three safe time thresholds, i.e., 30, 45 and 60 minutes. The sample application tested two scenarios - no mode shift and mode shift from car to bus - and introduced average speed and the number of successful evacuations of dependents to evaluate the performance of a relocation strategy. The safe evacuation time threshold was quite important for the relocation strategy; when it is adequate, relocating dependents benefits both those picking up dependents and the other vehicles in the network.

This dissertation contributes to the fields of evacuation modeling and transportation engineering, in general. This study investigates child pick-up, spouse gathering, and home gathering behavior during hypothetical incidents, and identifies characteristics associated with household decision makers that influence this behavior. The study also presents a model to integrate the behavior with road network simulation modeling; the combined model could be used to investigate the effects of gathering behavior on network traffic performance and identify

potential spatial and temporal bottlenecks. Finally, this work explored a strategy to facilitate household pick up chains by relocating facility dependents to more accessible site. The study can support any city evacuation plan development.

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Chapter 1 Introduction

Background

Recently, disasters occur frequently and cause devastating consequences. On March 11, 2011, a 8.9-magnitude earthquake hit northeast Japan, triggering a 10-meter high tsunami. More unfortunately, a nuclear power plant was damaged by the tsunami, and the subsequent nuclear explosion incident led to an evacuation of over 200,000 residents living in a 20 kilometer area around the plants (Norman, 2011). On December 26, 2004, a tsunami triggered by an undersea earthquake offshore of Sumatra, Indonesia, swept many coastal countries in the Indian Ocean including Indonesia, Sri Lanka, Thailand and India, over 283,000 were killed or reported missing, and become one of the deadliest natural disasters in recorded history (Levy & Gopalakrishnan, 2005). The terrorist attack of September 11, 2001 caused nearly 3000 fatalities and destroyed the 110-story Twin Towers of the World Trade Center and many other buildings at the site. These are all major no-notice disasters with devastating damages and are associated with evacuation.

No-notice incidents occur with no advance notice of time and place. Examples of no-notice evacuation include tsunamis, nuclear explosions, terrorist attacks, and hazardous materials (hazmat) releases. Hazmat release is one of the most frequent no-notice incidents in the United States; statistical data indicates that more than one major (serious) hazmat incident occurs every day in the US (Pearce, 2008), and some of them cause an evacuation. As no-notice incidents are sometimes accompanied by huge losses of property and human lives, special focus on evacuations from these kinds of incidents is necessary.

People respond and react to no-notice incidents differently than advance-notice incidents (e.g., hurricane). For example, family members are separated when a no-notice incident strikes during the daytime, they may seek to gather each other first and evacuate as a unit, and parents may head in the "wrong" direction to pick up their children from schools/daycare centers; this phenomenon has been addressed by previous researchers (Johnson, 1988; Murray-Tuite & Mahmassani, 2003; Sime, 1995; Zimmerman, Brodesky, & Karp, 2007). Johnson indicated that

"*no evidence appears of family members abandoning each other in order to facilitate their own survival*" (Johnson, 1988). These household pick-up and gathering activities generate more traffic to the road network or cause some vehicles to travel in directions opposite to general evacuation routes, which makes some well discussed strategies (e.g., phased evacuation) or widely used ones (e.g., contra flow strategy) infeasible in practice (Zimmerman, et al., 2007). Ignoring these actions leads to overly optimistic estimations of evacuation time.

However, these behaviors were seldom investigated previously due to insufficient data. Murray-Tuite and Mahmassani modeled the patterns of household members seeking each other and gathering in no-notice evacuations, but their work sought an optimal solution rather than modeling actual household behaviors (Murray-Tuite & Mahmassani, 2003). In reality, the optimum may not always be reached, so it is also important to find what factors influence individuals' decisions on gathering family members during an evacuation and how these actual behaviors affect evacuation efficiencies.

The interviews of individuals' responses to hypothetical no-notice incidents pertaining to picking up children and gathering family members was conducted by the University of Southern California and the Center for Neighborhood Technology (CNT) in the city of Chicago from July 2008 until January 2009. Thanks to the data collected during the interviews, it was possible to investigate actual household evacuation trip-chain behaviors.

Research Objectives

The objectives of this dissertation include:

- analyzing effects of characteristics (such as age, gender, household income) on household pick-up and gathering behaviors, based on the interviews;
- developing models to predict the probability of a household member picking up a child, or gathering family members;
- developing a procedure to generate household evacuation trip chains;
- integrating the generated trip chains with network simulation modeling to evaluate the effects of household pick-up and gather behavior on network traffic performance; and
- proposing a relocation optimization model to facilitate no-notice evacuations and evaluate the performance of generated strategies.

Organization of the Dissertation

The remainder of this dissertation is organized as follows. Chapter 2 reviews the previous studies on emergency evacuation, including selected human behavior studies, demand forecasting studies, and network modeling. Chapter 3 presents an analysis of child pick-up during daily routines and for daytime no-notice evacuation; this paper is currently under peer review. Chapter 4 provides a paper with the title of Household Gathering Chains in an Evacuation Model: Procedures and Case Applications and will be submitted in the near future. Chapter 5 discusses a strategy on relocating children in daytime no-notice evacuations; this chapter was organized into a paper titled Relocating Children in Daytime No-notice Evacuations: Methodology and Applications for Transport Systems of Personal Vehicles and Buses that was accepted for publication in the *Transportation Research Record*. Chapter 6 concludes the dissertation.

Chapter 2 Literature Reviews

Introduction

This chapter provides a general overview of previous studies pertaining to evacuation behavior and modeling. First, a thorough review of the literature on evacuation behavior is presented, followed by a review of evacuation demand generation and loading models. The final part reviews a variety of network evacuation models (simulation-based and optimization-based).

Evacuee Behavior

Behavior analyses for evacuees include investigating whether they evacuate, when they evacuate, where they are from, where they go to, and what mode they take to evacuate. Over the past several decades, social scientists investigated the factors that influence people's decisions to evacuate from natural disasters. Baker (1991) studied 12 hurricanes and found the five most important factors to influence the choice to evacuate: 1) risk level of the area, 2) action by public authorities, 3) type of housing, 4) prior perception of personal risk, and 5) storm-specific threat factors. Riad et al. (1999) found that, apart from individual characteristics, evacuation decisions are influenced by three social psychological processes: risk perception, social influence and access to resources.

Baker (1991) and Dow and Cutter (1998) pointed out that personal risk perception is one of key factors to evacuation decisions. People who feel safe staying at home tend not to evacuate, while those who feel unsafe do (Baker, 1991; Dow & Cutter, 1998). However, there are challenges to defining "feeling safe." Dash and Gladwin (2007) provided a detailed review of previous studies on how people perceive their personal risk. They pointed out that perceived risk is not only involved with the probability of events and the extent of consequences, but also related to people's social and cultural characteristics. White (1988) argued that risk perception is a function of environmental factors, hazard-related factors, economic effects, and an individual's social relations.

Baker (1991) observed that residence locations play an important role in deciding whether to evacuate: people residing in high-risk areas (e.g., low-lying coastal areas) are more likely to evacuate. West and Orr (2007) studied evacuation behavior based on a telephone survey of 785 Rhode Island voters (Rhode Island is located on the coast of the Atlantic Ocean), and the results showed that residents living close to the water are more likely to evacuate than those living inland. Lindell et al. (2005) drew similar conclusions using data from 2002's Hurricane Lili in Louisiana. In addition, housing affects evacuation decisions (Baker, 1991; Whitehead, et al., 2000). According to Baker (1991), residents living in mobile homes are more likely to evacuate than those living in other types of houses due to mobile homes' vulnerability to strong wind and falling objects. Gladwin and Peacock (1997), using data collected after Hurricane Andrew, found that residents living in multi-unit buildings are more likely to evacuate than those living in single-family houses, who tend to stay and protect their property.

Baker (1991) also stated that wording and dissemination of evacuation orders is of great importance in making evacuation decisions. People who receive a mandatory order are more likely to evacuate compared with a voluntary order (Whitehead et al., 2000). Warning messages or evacuation orders can be disseminated from government agencies to the public through a mix of sources including the media, emergency officials, friends, neighbors and relatives. The media, according to Baker (1991), is an important source to convey evacuation information. Gladwin and Peacock (1997) agreed with and emphasized this critical role of the media, especially television, in transmitting warning and evacuation orders. West and Orr (2007) again supported this argument and demonstrated that people are more likely to evacuate when they receive evacuation orders from government officials or the media. Sorensen and Mileti (1988) suggested that social networks are vital to warning dissemination and evacuation decision making. People tend to believe what they hear from their friends and family, and women and minorities are less likely to trust government and the media than others (West & Orr, 2007).

Accuracy in the warning message was thought to have a potential role in citizens' belief in subsequent warnings. "Crying wolf" syndrome refers to a phenomenon that people who experience a false alarm in the past are unwilling to evacuate in the future. Baker (1991) discussed the "crying wolf" phenomenon and found no clear evidence that false past experience affects future evacuation decisions. Later, Dow and Cutter (1998) examined human response to

two storms in South Carolina, Hurricanes Bertha and Fran, and found even though trust and confidence in emergency managers decreased from Hurricane Bertha to Fran, this decrease did not affect household evacuation decisions. Another issue termed "shadow" (or spontaneous) evacuation, pertains to people living in low-risk areas who, influenced by evacuation from high-risk and moderate-risk areas, choose to evacuate even though they may not be required to do so (Baker, 1991). Shadow evacuees cause more severe traffic congestion and therefore increase clearance time. Shadow evacuation was observed during Hurricane Floyd in north Florida and Georgia and Hurricane Rita in Texas (Dash & Gladwin, 2007).

Baker (1991) and Dow and Cutter (1998) suggested that household demographic factors, such as age, gender and race/ethnicity, are not associated with evacuation decisions. However, Whitehead et al. (2000), Gladwin and Peacock (1997), Bateman and Edwards (2002), Solis et al. (2010), and others found these factors significant to evacuation decisions. For example, women are more likely to evacuate than men (Bateman & Edwards, 2002; Gladwin & Peacock, 1997); the presence of children increases the probability of evacuation (Gladwin & Peacock, 1997, Solís et al., 2010); and households with pets are less likely to evacuate (Solís et al., 2010, Whitehead et al., 2000).

Bateman and Edwards (2002) conducted a series of analyses based on a household survey for Hurricane Bonnie and found that women are more likely to evacuate for hurricanes because of "their greater exposure to certain objective risks and their more acute perception of subjective risk." In other words, women are more likely to live in high-risk areas, such as living on a barrier island, in a mobile home, close to water or in a storm surge area, due to their lower incomes; meanwhile women perceive greater risks from coastal flooding and wind than men; both of these factors contribute to women's greater propensity to evacuate from hurricanes. Moreover, according to Bateman and Edwards (2002), women's higher likelihood of evacuation is partly because of their responsibility towards children and other dependent household members. Their findings are consistent with earlier disaster studies, which found that women are more likely to feel vulnerable to disasters than men, and this vulnerability results from women's lack of financial resources, their care giving responsibilities, a lack of mobility and social isolation (Bolin, Jackson, & Crist, 1998; Enarson & Morrow, 1998; Fothergill, 1996). Bateman and Edwards's (2002) work, specifically, supported the arguments that gender per se does not

explain why women are more likely to evacuate than men, instead, gender differences exist in other factors that essentially influence evacuation intentions and abilities.

Concerning race/ethnicity differences in disaster evacuation, some literature found no significant correlations between race/ethnicity and evacuation outcomes (Dow & Cutter, 1998), while others found the opposite. Gladwin and Peacock (1997) concluded that blacks (or African Americans) residing in a dangerous zone are less likely to evacuate than Anglos. One interesting finding is that race is a significant factor to determining evacuation decisions without controlling for risk indicators (objective and perceived); however, it becomes insignificant with risk indicators included; this is consistent with West and Orr's (2007) finding that race is significantly associated with risk perception, but does not significantly affect evacuation actions. Thus, race may affect evacuation behavior through its influence on personal risk perception. Gladwin and Peacock (1997) indicated that ethnic minorities' lower likelihood to evacuate is "probably a result of economic conditions rather than race or ethnicity per se in that minorities may have fewer evacuation options." These two statements are not contradictory because personal risk perception is tied to economic status.

Fothergill et al. (1999) presented an in-depth review of disaster research that addresses race and ethnicity issues. They generalized that minority groups are more vulnerable to natural disasters than whites, because of problems like language, housing, social isolation, and cultural insensitivities. For example, blacks are more fatalistic about earthquakes than whites; white males are the least worried about disaster risks; and, more blacks lives in older, poorly built houses, which expose them to greater dangers when disasters strike. Researchers argued that minorities' vulnerability to disasters is mainly a result of economic status and resources and suggested addressing class issues rather than race/ethnicity issues. Elliott and Pais (2006) examined how race and class influence human responses to hurricanes using the data collected from over 1200 Hurricane Katrina survivors, and the results revealed that both race and class are the strong predictors and "neither can be readily reduced to the other." Specifically, their findings indicated that low-income blacks, not blacks or the low-income population in general, were the least likely to evacuate through the disaster. Some literature indicated ethnic differences exist in other aspects of disaster response, such as warning communication: Mexican-Americans

are more likely to use social networks for warning information than whites and blacks (Blanchard-Boehm, 1997; Perry & Mushkatel, 1986).

Gladwin and Peacock (1997) indicated that the presence of young children in the home increases the propensity to evacuate because of parents' intention to protect children from danger; this finding was confirmed by Solis et al. (2010) who investigated household hurricane evacuation choice using survey data in Florida. According to Baker (1991), age is believed to be a critical factor to influence evacuation decisions because of restricted mobility of the elderly; Gladwin and Peacock (1997) supported this argument by finding that households with the elderly are less likely to evacuate. However, Bateman and Edwards (2002) found no significant relationship between age and evacuation actions for both men and women. As for wealth, according to Gladwin and Peacock (1997), households with higher incomes are more likely to evacuate because they are less constrained by transportation and can afford to stay in hotels; however, since households with higher incomes usually live in well-constructed houses and own more valuable goods that they may want to stay and protect, they display lower propensity to evacuate, as concluded by Whitehead (2003). Thus, the effect of income is potentially dependent on the situation and other variables included in the model.

Whitehead et al. (2000) studied how social, economic, and risk-related factors influence destination choice behavior during a hypothetical hurricane based on data from a telephone survey of North Carolina coastal residents. The results revealed that females, non-whites, pet owners, and those with more education are less likely to choose a shelter, and high-income households are more likely to stay in hotels/motels. Their findings are consistent with the previous finding that the poor, minorities, and families with the young and the elderly tend to stay at relatives' homes or a shelter, while others tend to choose hotels/motels (Drabek & Boggs, 1968; Perry & Mushkatel, 1986).

Most of the above-mentioned findings are based on data collected for hurricane evacuations; however, each type of disaster has its unique characteristics affecting evacuation behavior. Charnkol and Tanaboriboon (2006) investigated evacuee behavior in tsunami evacuations based on data collected in Baan Namkhem, Phang-Nga Province, Thailand after the Indian Ocean tsunami of December 26, 2004, and found six factors (education level, ownership of the residence, distance to the nearest shore, knowledge of the disaster, number of household

members, and status of respondents) statistically significant, where distance to the nearest shore and knowledge of the disaster were the most influential factors affecting evacuation patterns.

These studies all pertained to identifying factors related to the decision to evacuate or not. These factors could potentially help predict the number of evacuees based on characteristics of the population, but including these factors was not common practice for past studies related to the estimation of total demand. The next section examines literature on both total demand estimation and departure times.

Evacuation Demand Model

Current practices of estimating time-dependent evacuation demand are completed in two steps: firstly, estimate the total number of evacuees, and secondly determine their departure time (Wilmot & Mei, 2004). Evacuation participation rates (the proportion of households expected to evacuate) are most commonly used to estimate the total number of evacuees and can be determined subjectively based on past experience; logistic regression is another widely-used method to estimate whether a household would evacuate or not (Whitehead, et al., 2000; Wilmot & Mei, 2004). A response curve that represents the percentage of evacuees in each time period is typically used to conduct the second step (Fu & Wilmot, 2004); it could take a sigmoid or S shape or a Rayleigh distribution (Lewis, 1985; Tweedie et al., 1986).

Recently, a few new methods were developed for evacuation demand estimation. Wilmot and Mei (2004) applied artificial neural networks to estimate evacuation demand, and compared them with participation rates and logistic regression using a data set of evacuation behavior collected from southwest Louisiana after Hurricane Andrew. In their work, three types of neural networks were tested, i.e., a feed-forward neural network, a probabilistic neural network, and a learning vector quantization neural network. The results showed that logistic regression and neural network models estimate evacuation demand more accurately than participation rate models. Wilmot and Mei concluded that it is hard to estimate evacuation demand accurately.

Fu and Wilmot (2004) considered the decision to evacuate from an approaching hurricane as a series of binary choices over time and presented a sequential binary logit model to estimate the probability that households will evacuate in a certain time period. The proposed determinants include households' socioeconomic characteristics, hurricane features, and policy decisions

made by authorities. Data collected in southwest Louisiana after Hurricane Andrew were used, where 85% of the data were used to estimate the demand model and the remaining 15% were used to test the model. The results showed that the proposed model is capable of estimating dynamic evacuation demand (Fu & Wilmot, 2004).

Yazici and Ozbay (2008) performed an in-depth sensitivity analysis of three selected evacuation demand models: S-curve, Rayleigh distribution (Tweedie's approach (Tweedie, et al., 1986)), and sequential logit. The S-curve is the most popular model in evacuation studies and it has been used in some evacuation software packages, such as MASSVAC; Tweedie's approach is relatively simple and mainly relies on expert judgment; the sequential logit model is a promising model because of its ability to capture the individual decision process and reflect factors affecting evacuation behavior. These three models were tested on the Cape May network. The results indicated that different loading curves result in significantly different evacuation performance, measured by network clearance time and average travel time; therefore, Yazici and Ozbay (2008) suggested the demand models should be used carefully.

Chiu et al. (2007) assumed that in a no-notice incident, the evacuation starts immediately after the occurrence of the incident, and all people inside the dangerous zone are evacuees and loaded to the network at the beginning of evacuation simultaneously.

Total demand and departures times are important inputs to transportation simulation and optimization models, which are discussed in the next section.

Evacuation Models

Historically, a huge tragic disaster aroused extensive attention to general evacuation research and specific concerns relevant to that particular disaster. The nuclear reactor incident at Three Mile Island in 1979 drove development of many evacuation models for power plants including NETVAC (Sheffi, Mahmassani, & Powell, 1982) and DYNEV (KLD, 1984). Hurricane Andrew in 1992, the most expensive natural disaster in U.S. history until Hurricane Katrina in 2005, shifted the research interests to hurricane evacuation and led to significant achievements in the 1990s. The Oak Ridge Evacuation Modeling System (OREMS) was developed by Oak Ridge National Laboratories (ORNL) during this period (ORNL, 1998). Later, terrorist attacks such as the September 11 attacks in 2001, Madrid train bombings in 2004, and London underground

attacks in 2005, evoked great interest in investigating man-made or no-notice disasters. Hurricanes Katrina and Rita in 2005 hit the southern United States and caused long-lasting destructive effects. Failing to evacuate the carless population triggered interests in carless evacuations.

Evacuation studies, according to scopes and features of impacted areas, fall into five general categories: regions, neighborhoods, buildings, ships and airplanes (Church & Cova, 2000). The previous studies on regional and neighborhood evacuation are involved in the subject of this dissertation and reviewed here. Regional (urban) evacuation models can be classified into aggregate models and disaggregate models. An aggregate model investigates a group of vehicles as a whole, while a disaggregate model evaluates each individual driver's behavior. An aggregate model overlooks the differences of individual driver's behavior among the population.

Most existing evacuation models were developed on an aggregate level and simulation-based (macroscopic), such as NETVAC (Sheffi, et al., 1982), DYNEV (KLD, 1984), and MASSVAC (Hobeika & Jamei, 1985). Sheffi et al. (1982) developed NETVAC to estimate evacuation time from areas surrounding a nuclear power plant. NETVAC can handle large-scale evacuation scenarios. DYNEV was developed by KLD Associates in the early 1980s for the Federal Emergency Management Agency (FEMA) to simulate nuclear power plant related evacuation (KLD, 1984). DYNEV is capable of estimating network clearance time for urban-size populations. Hobeika et al. (1985) developed MASSVAC to simulate the evacuation process on a road network on a macroscopic level under a hurricane evacuation scenario. MASSVAC can estimate the network clearance time and evaluate bottlenecks' impacts on evacuation performance.

A number of evacuation decision support systems were developed based on traffic simulation models since the 1990s. Hobeika et al. (1994) developed Transportation Evacuation Decision Support System (TEDSS) based on MASSVAC, to generate and evaluate evacuation plans for nuclear plant accidents. TEDSS has a knowledge-based system that stores expert evacuation rules, disaster features, and network characteristics to evaluate simulation results. TEDSS also allows users to view outputs such as optimal evacuation routes graphically. In the mid-1990s, Oak Ridge National Laboratory (ORNL) developed the Oak Ridge Evacuation Modeling System (OREMS), based upon traffic simulation models (e.g. CORSIM) from DOT

(ORNL, 1998). OREMS is capable of modeling large-scale evacuation scenarios, such as hurricanes and nuclear power plant events, and cross-applies an evacuation strategy through different types of disasters. OREMS can be used to estimate clearance time, identify evacuation bottlenecks, and assess the effectiveness of evacuation management strategies, such as traffic controls.

Most of the existing models, as mentioned above, are either designed for small-area evacuation or are not microscopic. Micro-simulation simulates movements of a vehicle though a network over time and can provide more detailed results, as does mesoscopic simulation. However, as micro simulation emphasizes great detail for both vehicles and networks, it is difficult to apply it to a large-area evacuation with constraints of current computation capabilities. Few existing models are both microscopic and able to deal with a regional evacuation (Cova & Johnson, 2002). Recently, some studies have been conducted to fill the gap. Lammel and Nagel (2009) presented a multi-agent based technique to model a large-scale evacuation on the microscopic level. In this model, each evacuee is treated as an individual agent, each agent determines its evacuation plan independently, and all agents' plans are executed simultaneously on a simple queue model. The physical road system is modeled as queues, rather than represented by a road network composed of nodes and links, as general micro simulation traffic models do. The queue model only takes speed and bottleneck capacities into consideration and allows the investigation of bottleneck effects on evacuation time. The model was applied to Padang, a city of Indonesia that faces a high risk of being flooded by tsunami, and was capable of solving large-area evacuation cases (Lammel et al., 2008). Argonne National Laboratory is building an activity based model using TRANSIMS to simulate the emergency evacuation process of the Chicago metropolitan area and its impact on the Chicago Business District (ANL, 2008). TRANSIMS is another agent based modeling tool with the capability of simulating large area traffic situations on a second-by-second level (AECOM, 2010).

Optimization programming is a way to avert the difficulties of large-scale micro simulation modeling. Liu et al. (2006) applied the cell transmission model (CTM) to an evacuation study, in order to handle large-area evacuations and provides a candidate set of optimal evacuation plans as input for simulation-based evacuation systems. The CTM was developed by Daganzo (1994) to dynamically represent road traffic analogical to hydrodynamic

theory and first formulated as a linear programming problem by Ziliaskopoulos (2000). Chiu et al. (2007) integrated three evacuation decisions (i.e. evacuation destination, routes and departure time) into one CTM based unified optimization model. Tuydes and Ziliaskopoulos (2004) formulated an optimization model to represent network evacuation contraflow operations, based on a system-optimal dynamic traffic assignment method.

Most other studies on optimization based evacuation models were mainly developed to solve a specific problem. Murray-Tuite and Mahmassani (2003) presented a series of linear integer programming formulations to model household gathering behavior for no-notice evacuation. In their work, the best meeting point for each household and activity trip chain of picking up are determined. They later incorporated this household behavior model with a mesoscopic traffic assignment simulation tool, DYNASMART-P (Dynamic Network Assignment Simulation Model for Advance Road Telematics) (Murray-Tuite & Mahmassani, 2004).

One area of evacuation modeling that extensively utilizes optimization programming technique is to determine shelter locations. The locations of shelters may influence network clearance time significantly under hurricane evacuations. Sherali et al. (1991) investigated this issue by developing a location-allocation model to determine optimal shelter locations among potential candidates to minimize congestion-related evacuation time. They developed a heuristic and an exact enumeration algorithm to solve the model, tested it on the Virginia Beach network and found both approaches applicable to reality. Yazici and Ozbay (2007) considered the stochastic feature of road capacity during an evacuation, (e.g. a certain section of road may be damaged totally or partially by a hurricane or flood), to evaluate performance of fixed shelter locations. They incorporated probability of road capacity into a cell-transmission based system optimal dynamic traffic assignment (SODTA) model to test impacts of flood probability on shelter locations, importance, and capacity. The results indicated that accounting for flood probabilities can change favorable shelter locations. Kongsomsaksakul et al. (2005) applied game theory to the shelter-location problem and considered the influence between authorities and evacuees as a Stackelberg game. A bi-level programming model was developed: the upper-level determines numbers and locations of shelters to minimize the total evacuation time, and the lower-level assigns evacuees to shelters and routes. A genetic algorithm (GA) was proposed to

solve the model. The existing studies on evacuation destination choice model are mainly for hurricane situations; no-notice evacuation destination choice should be further explored.

Most of the above mentioned models are at the aggregate level; they do not take into account an individual's behavior while modeling the evacuation progress. Stern and Sinuany-Stern (1989) incorporated some behavior-related parameters, including diffusion time of evacuation instruction and individuals' preparation time, in a microscopic simulation model for an urban evacuation. Later, Sinuany-Stern and Stern (1993) developed the SLAM Network Evacuation Model (SNEM) based on this behavioral-based model to test the effects of traffic factors (e.g. household size, car ownership, and intersection traversing time) and route choice parameters on network clearance time.

Not much attention has been paid to neighborhood evacuation during the last twenty years, compared with region-scale evacuation or building evacuation (Church & Cova, 2000; Church & Sexton, 2002; Cova & Johnson, 2002). Evacuating small areas or neighborhoods may be difficult due to high ratios of population to exit capacity and could be a bottleneck of a network (Church & Cova, 2000). Cova and Church (1997) developed an evacuation vulnerability model using integer programming to identify the neighborhoods with potential difficulties in an evacuation (vulnerability to a disaster). This evacuation vulnerability model has the potential to be integrated with existing GIS-based evacuation models. This model was improved and applied to Santa Barbara, California (Church & Cova, 2000) and later tested by the microscopic traffic simulation model Paramics on the Mission Canyon neighborhood, and the simulation resulted in the similar conclusions with the evacuation vulnerability model (Church & Sexton, 2002).

To summarize, a large body of previous studies has focused on human evacuation behavior and network evacuation modeling and provided rich and valuable contributions to the field. However, there are still some gaps that need to be filled, for example, household evacuation behavior or family gathering, and integrating enriched behavior studies and network modeling studies, which triggered this dissertation research. The dissertation is motivated to fill the gap of household gathering behavior in evacuation cases and answer the questions of 1) how people react to pick up and gather family members when a disaster strikes; 2) how these actions affect evacuation efficiency generally.

Chapter 3   Analysis of Child Pick-Up during Daily Routines and for Daytime No-Notice Evacuations

This chapter presents a paper that is currently under peer review. It was jointly written by Sirui Liu, Pamela Murray-Tuite, and Lisa Schweitzer. Sections in italics were primarily written by Dr. Schweitzer.

Abstract

In a no-notice disaster (e.g., nuclear explosion, terrorist attack, or hazardous materials release), an evacuation may start immediately after the disaster strikes. When a no-notice evacuation occurs during the daytime, household members are scattered throughout the regional network, and some family members (e.g., children) may need to be picked up. This household pick-up and gathering behavior was seldom investigated in previous work due to insufficient data; this gap in our understanding about who within families handles child-gathering is addressed here. Three hundred fifteen interviews were conducted in the Chicago metropolitan area to ascertain how respondents planned their response to hypothetical no-notice emergency evacuation orders. This paper presents the influencing factors that affect household pick-up and gathering behavior and the logistic regression models developed to predict the probability that parents pick up a child in three situations: a normal weekday and two hypothetical emergency scenarios. The results showed that *both* mothers and fathers were more likely to pick up a child under emergency conditions than they were on a normal weekday. For a normal weekday, increasing the distance between parents and children decreased the probability of parents picking up children; in other words, the farther parents are from their children, the less likely they will pick them up. In an emergency, effects of distance on pick-up behavior were significant for women, but not significant for men; that is, increasing the distance between parents and children decreased the probability that mothers pick up a child, but had a less significant effect on the fathers' probability. Another significant factor affecting child pick-up behavior was household income when controlling for distance. The results of this study confirm that parents expect to gather children under emergency conditions, which needs to be accounted for in evacuation planning;

failure to do so could cause difficulties in executing the pick-ups, lead to considerable queuing and rerouting, and extend the time citizens are exposed to high levels of risk.

KEYWORDS: No-notice evacuations; Child-chauffeuring; Family-gathering; Logistic regression; Human behavior

Introduction

For a daytime no-notice evacuation, household members are likely to be scattered throughout the regional network. When the evacuation distance is too far to walk, family members are likely to gather carless/non-driving family members (e.g., children) and evacuate as a single unit. This behavior has been observed in prior studies of threats with some advanced warning (Perry et al. 1981; Sallee 2005; Drabek 1999; Drabek and Boggs 1968). Zimmerman et al. (2007) include parents picking up their children from schools, relatives, homes, or daycare centers in the impacted area and heading in the "wrong" direction to gather their family or friends in their discussion of "self-motivated" actions. These "self-motivated" actions may conflict with evacuation plans, generate extra traffic to the road network and cause some evacuees to travel in a direction opposite the planned evacuation routes, which make some well discussed strategies (e.g., phased evacuation) or widely used ones (e.g., contra flow) infeasible in practice (Zimmerman et al. 2007). Ignoring these "self-motivated" actions also leads to overly optimistic estimations of evacuation time (Murray-Tuite and Mahmassani 2004). Therefore, exploring these behaviors is important for no-notice evacuation planning and management.

We find in the analyses presented in this manuscript that the gathering activities reflect differences in gendered roles for male and female parents. *Differences in travel behavior by gender have been a robust finding across virtually every aspect of travel behavior ranging from driver risk-taking, mode choice, travel time and distance, and the values placed on time, delays, and on-time arrival for everyday travel decisions (Lopata 1980; Rosenbloom and Burns 1993; Rosenbloom and Burns 1994; Kwan 1999; Lam and Small 2001; Crane 2007). Just as everyday travel behavior exhibits distinct differences by gender, research has shown that gender and its associated roles affect the choices and behavior made during disasters and evacuation (Enarson 1998). Research has also shown significant differences among women by ethnicity, health status, and class differences that, again, appear to affect both everyday and emergency travel*

(Johnston-Anumonwo 1992; McLafferty and Preston 1992; Fothergill 1999; Rosenbloom 2001; Hutchinson 2005).

Most researchers explain gender differences in transport with the Household Responsibility Hypothesis (HRH), which attributes differences in travel demand to differences in household responsibilities and, in particular, caring work - work undertaken to care for family members, particularly children (Johnston-Anumonwo 1992). Although women have increased their hours spent in the paid workforce, studies have consistently found that while males have increased their participation in household unpaid work over the past decades, they still do less, and they have done so in lower proportion to women's increases in paid work (Hochschild & Machung 1989; Bianchi et al. 2000; Greenstein 2000; Coltrane 2000; Bittman et al. 2003; Parkman 2004).

Because of the robustness of the findings from previous decades, the differences in caring responsibilities have become the accepted wisdom in explaining differences in women's travel behavior. Empirical work that actually measures the differences in travel related to caring work, however, is scarcer than the conventional wisdom allows. Since the ground-breaking work done in the early 1990s by Hanson and Pratt (1995), the research has only infrequently studied the household allocation decisions that connect caring responsibilities, household work, and travel behavior. In addition, Giuliano and Schweitzer (2009) note in a recent review that, since the pioneering studies about women's travel in the 1970s, 1980s, and 1990s, policy has been rich with anecdotes, particularly about single mothers, but short on research that measures the values and barriers that mobility can bring in support of parents. The policy and planning response to difference has been weak, and what little contemporary research exists on women's travel shows that differences by gender and ethnicity have lessened but not disappeared (Johnston-Anumonwo 2001; Crane 2007; Crane and Takahashi 2009).

Because so little data and empirical analysis exist about how women's caring work influences their travel and vice versa, it is difficult to interpret what the persistent differences in travel distance, mode, and timing mean in terms of women's lives or the mobility policy and planning that best supports them. Caring work occurs within family, neighborhood, and professional networks; it is work sometimes taken on by choice, sometimes by necessity, and it is often shared in complex and unexpected ways.

This manuscript fills a gap in our knowledge about how families allocate the caring work that includes mobility, such as taking children to school. Using in-depth, structured interviews with 233 parents and other caregivers throughout the Chicago region, we collected data about the daily practices and the arrangements that families have for picking up dependents in case of a no-notice event during the day. Key to the data collection strategy was the spatial and socio-demographic oversampling of a predominately Latino, low-income community in Logan Square, a neighborhood that is well-served by public transit, to contrast with families sampled more randomly throughout the entire region. We have gathered detailed information about the social and familial practices surrounding care work and mobility. Using a reduced form of the data, we constructed discrete choice models for both everyday and emergency/evacuation plans for transporting dependents. The proposed evacuation behavior models are among the first to address specifically the influences of household characteristics on child-related travel in evacuations.

Our manuscript begins with an examination of the previous research on the allocation of household travel decisions and the influences of household characteristics and behavior on evacuations. Hypotheses investigated in this study are listed at the end of Section 2. The subsequent sections describe the data collection strategies and salient variables. Then, a series of discrete choice models that describe families' choices about transporting dependents during both everyday and emergency conditions are presented and discussed. In the last section, we provide conclusions and discuss the implications for transport policy and practice.

Prior Research and Theory

"Self-motivated" evacuation behaviors (Zimmerman et al. 2007) were seldom investigated in previous work due to a lack of data on this subject. Murray-Tuite and Mahmassani (2003, 2004) were among the first to model mathematically household members gathering prior to departing the dangerous area. In their work, linear integer programs were used to derive optimal meeting locations and to sequence and assign drivers to pick up sites (Murray-Tuite and Mahmassani 2003). Their work was optimization-based rather than an empirical behavior model.

However, empirical behavior models have been developed by numerous social scientists in a variety of disaster contexts to investigate the household's decision of whether to evacuate or shelter in place. They found the evacuation/shelter decision to be associated with household

characteristics, such as gender of the respondent, education level, household income, household size, location of household's residence, and the presence of children (Bateman and Edwards 2002; Elliott and Pais 2006; Gladwin and Peacock 1997; Mozumder et al. 2008; Solís et al. 2010; Whitehead et al. 2000). The findings included that women are more likely to evacuate (Bateman and Edwards 2002; Gladwin and Peacock 1997; Mozumder et al. 2008); the presence of children makes evacuation more likely (Gladwin and Peacock 1997; Solís et al. 2010); the presence of the elderly makes evacuation less likely (Gladwin and Peacock 1997); households with higher income are more likely and more able to evacuate (Gladwin and Peacock 1997); large family size decreases evacuation likelihood (Gladwin and Peacock 1997); ethnic minorities (e.g., Black and Hispanic) are less likely to evacuate (Elliott and Pais 2006; Gladwin and Peacock 1997); housing type affects decisions to evacuate, i.e., people living in single-family dwellings are less likely to evacuate than those living in multi-unit buildings (Baker 1991; Gladwin and Peacock 1997; Whitehead et al. 2000); and households with pets are less likely to evacuate (Mozumder et al. 2008; Solís et al. 2010; Whitehead et al. 2000). With the exception of Mozumder et al. (2008) who studied wildfires, the evacuation decision was considered in the context of hurricanes.

In the context of our hypothetical no-notice evacuation, a small number of respondents indicated that they plan not to evacuate (even assuming they were in a mandatory evacuation zone); however, these refusals came generally from singletons and elderly respondents. No parent or householder with children refused to plan through the two evacuation scenarios. Thus, the decision to evacuate was treated as a given, and we focused our evacuation models on the reported gathering of family members. To the extent possible, the variables identified as influencing evacuation decisions (listed above) were considered in these models. The evacuation decision factors were combined with those long associated with day-to-day child-serving (drop-off/pick-up) behavior to aid in the determination of influence of the travel context.

In day-to-day travel studies, child-serving travel was more likely to be conducted by women than their male counterparts due to their roles of being primarily responsible for childcare (Bhat 1996, 2001; McGuckin and Murakami 1999; Meloni et al. 2009; Primerano et al. 2008). Mauch and Taylor (1997) examined the combined influences of gender and race/ethnicity on child-serving travels during the journey to work based on detailed trip diary data from a 1990 survey of San Francisco Bay Area residents. The authors indicated that gender variations in

child-serving travel are highest among Hispanics and whites and lowest among Asians and Pacific Islanders; they concluded that child-serving trips are significantly correlated with gender but only weakly related to race/ethnicity. Besides gender and race/ethnicity, Mauch and Taylor (1997) examined the effects of other factors on child-serving stops on the commute to work and found that the presence of children between 0-15 years old and the number of children in this age group increased the likelihood of an adult worker chauffeuring children during the work commute; the presence of a stay-at-home adult, no matter male or female, reduced the propensity of making child-serving stops for adult workers in the household; and the propensity of making child-serving stops increased with travel time to work.

One of the most prevalent explanations for why women receive a greater share of unpaid household work, including child serving travel, concerns their lower earnings and household optimization decisions. Becker (1991), in deriving one of the most widely cited theories from economics, assumes altruism: the allocation of work within households is undertaken largely to optimize the outcomes for the family unit, and since male earners in general make more than female earners, the family is better off substituting the lower wage earner's time for the necessary but unpaid work associated with making a household run--like toting dependents to various activities. A variant of this theory suggests that households optimize this allocation based on who has time availability, flexibility, or capacity to respond to household needs (Coverman 1985).

However, as feminists, sociologists, and game theorists note, who has time, money, and flexibility can depend at least partially on power and social privilege. A second theory from sociology accepts that household allocations are based on relative earnings, but is somewhat less optimistic about the role that higher earnings play in conveying power in allocation decisions. Bargaining-exchange theory holds that though family members do care about the well-being of the family unit, they also remain sufficiently self-interested that they bargain to their own advantage within some degree. The higher wage earner enjoys a superior bargaining position, and thus can and does use that power to demand less household responsibility--a proposition that has been the focus of substantial empirical research among sociologists (Heer 1963; Brines 1994; Greenstein 2000; Bittman et al. 2003; Parkman 2004; Gupta 2007).

Whichever of these theories holds, the outcomes should be roughly the same for women's travel demand because, in both cases, higher male earnings translates to greater household responsibility for the women. Niemeier and Morita (1996) posited that if economic theories are correct, two people of different genders with the same income levels should have little difference in the household-related travel behavior. Their model of shopping trip duration suggests that, in their sample, men and women spend roughly the same amount of time on personal business and leisure related trips, but that women's shopping trip duration is roughly twice that of male household members, and that they undertake more household-supporting trips overall. Most research backs up the theory that differences in household responsibilities, regardless of what drives them, play out across urban geography and mobility, with women having shorter commutes and treating home and work locations as more contingent on their household responsibilities (Hanson and Pratt 1995; see Turner and Niemeier 1996 for an overview of the research until 1996 and Blumenberg 2004 for an update and critique).

Empirical contradictions preclude ending the discussion there despite the consensus in the literature. Women of color have not had shorter commutes, at least not in terms of time, which suggests that white women's ability to commute from a shorter distance or time reflects an advantage compared to women of color in metropolitan labor markets. Shorter commutes can thus indicate privilege among white women. Furthermore, if the difference in commuting distance and time simply reflect wage inequality, the differences between men and women's commutes should go away as women move into higher earnings. There is some evidence that this is happening, albeit slowly, from one generation of women to another, but that differences in commutes by gender and ethnicity persist (Crane 2007).

The sociological research on household responsibilities again supplies one possible answer: that a) the bargaining-exchange theories of household work allocations function differently between men and women within the same household, and b) the bargaining dynamics are different by class and culture as well. Brines (1994) demonstrates that women's time spent on household responsibilities decreases as their income increases, and men's household work increases as their spouse's income begins to equal theirs. That would be as expected. However, when women's income eclipses their partner's, the male participation in household work decreases, suggesting that male partners reject trading their unpaid work if it entails a financial

dependence on a female spouse—a display of gendered behavior that contradicts the bargaining and economic rationale for higher home workloads. Greenstein (2000) updates the study and finds similar effects, but he interprets the results somewhat differently and suggests the difference may derive from the fact that families in this situation purchase services rather than allocate them internally. Bittman et al. (2003) describe similar findings and suggest that because women's baseline levels of housework in the aggregate start off so much higher than their partners', the gap remains as women's incomes become quite high. Even if high-income women and low-earning men are hiring out household services, women at lower relative wage levels seem to trade unpaid work for a share in family income when male partners in commensurate positions do not. That suggests there is a gender imbalance in individual's economic dependency on the partnered relationship. Moreover, the fact that men in reversed earning roles do not step up the same way could indicate, quite simply, higher levels of perceived entitlement among both partners, and thus men bargain more than do women in similar positions.

Bianchi et al. (2000) counter that purchased services and fewer hours spent on housework in total also explain why male participation declines with high-earning female partners, and that relative wage substitution explains the rest. Gupta (2007) finds that women's absolute wages and earning power--rather than their earnings relative to their partners'--is a better predictor of the amount of household work that women do. However, Gupta's study (and all of its predecessors) missed looking at what, given the theory, seems to be a high probability for a threshold effect among female wage earners: once a woman reaches a certain income, wealth, or skill level, she is unlikely to feel economically dependent on her partner. Below that threshold, however, the personal risks and risks for one's children associated with bargaining to the displeasure of a higher-income partner are more apparent to all bargainers.

Fagnani (1987) presaged some of these variables at the household level within the travel behavior research to explain differences in commute times and distances among French working mothers. This study sorted out differences among higher-paid, skilled and lower-paid, unskilled labor and found that higher-skilled women were able to schedule more to their discretion and obtain more help in handling home errands than lower-skilled, working women. The connections between women's unpaid household work, segregation in the paid labor force, and their mobility

also appears in work by Hanson and Pratt (1990) to suggest that the bargaining position at home affects women's prestige and potential.

In a critique of both the empirical research and theories surrounding household work, Eichler and Albanese (2007) raise three issues salient to the connection between household responsibilities and mobility. First off, they note that household responsibility research tends to assume that household work is done by husbands and wives, and that it is done within the home or at the home site. Travel behavior research addresses this critique somewhat by showing that household-serving trips outside the home are themselves part of the portfolio of necessary, unpaid work within households. However, the husband-and-wife dichotomy is a problem for mobility research in that, even if Greenstein (2000) and Bianchi et al. (2000) are correct and the work is being hired out, <u>somebody</u> is still doing that work and <u>somebody</u> probably requires mobility to do it--even if those trips are being taken by nannies and other service workers, predominantly lower-status women and women of color, whose work is largely ignored within the discussion on travel (Hondagneu-Sotelo 2001).

Eichler and Albanese (2007) raise two additional critiques that we shall discuss as components of the same gap within the research. First, they indicate that the household responsibility research tends not to differentiate among different types of unpaid tasks. Eichler and Albanese note that caring for adults--a large part of everyday family life for many--is seldom counted in household time surveys. Second, most of the household responsibility research treats all types of unpaid household work as repetitive drudgery. Instead, both women and men take on some types of unpaid work out of love and enjoyment as well as out of obligation. Treating all the tasks the same ignores that couples may specialize at home according to things they prefer to do (or simply dislike the least), or because they enjoy doing it. Taking children to the beach--though child care and potentially tiring--is much different than cleaning the refrigerator or changing adults' diapers.

Health, education, and family researchers distinguish between caregiving or "care work" and other types of household tasks for these reasons. Transportation related to caring, and women's engagement with it, may be much different than the errands they run to keep the household going. In a survey of the existing studies conducted by Coltrane (2000), women reported roughly twice the amount of time spent on housework, childcare, and eldercare than did

male respondents. The research by the early 2000s found that while male partners have increased their participation in all forms of uncompensated work for the family, they appear to have taken on time-flexible tasks more readily scheduled at their discretion and around their regular work hours. Women, by contrast, still performed much more inflexibly scheduled care work, such as making meals, picking up children, or taking dependent elders to appointments (Coltrane 2000). Researchers in transportation have drawn on these differences between household work and time flexibility to explain why working women report higher values of travel time reliability (Lam and Small 2001) and exhibit greater sensitivity to transport service quality inconsistencies (Rosenbloom and Burns 1994).

In addition to the practical differences between care work and other unpaid tasks, different types of care work take different emotional and physical tolls on the caregiver. Coltrane's survey of the sociological research and the voluminous research on elder care from health and medicine show that women undertake all forms of care work more than their male partners do. But even as they do so, women rank child-related care as much more enjoyable than they do either elder care or spousal care. There may be some social desirability bias in the responses; there is social pressure for women to report devotion and care, particularly for spouses and children, but still it seems reasonable to go with common sense here: caring for children has its ups and downs, but on the whole it is something women value and enjoy as well as being something that they must do.

We do not have a lot of information on how child-related transport fits into the spectrum of care work, emotional tolls, and personal feelings of enjoyment. Bostock (2001), in an excellent critique of the class presumptions within public health research on women's walking, noted that for impoverished women who had no choice but to walk, the leisure-time, recreational arguments prevalent in that literature made little sense. While some envision walking as an active, happy family activity, such framings are bound to community contexts and women's lives, which are, in turn, affected by race and class. Instead, for impoverished women, walking with children, often bored and hungry, was yet another physically demanding chore in a long day. In another example, Hutchinson (2005) relates how black women and children treated LA's bus transit as a time for connecting with each other and the city--at the same time that white women's narratives about the bus primarily focus on safety.

Our study takes up these questions about child-related transport specifically as care work in families nested within different class and culture structures. We cover six salient hypotheses:

a) Women handle more transport-related care work than men on a normal workday;

b) In cases of emergency at the school or evacuation, parents form their plans based on their everyday roles with regard to transport-related care work;

c) Working women's job locations will be closer in time and distance than men's work locations to child and home locations;

d) Transport-related care work surrounding children will occur disproportionately by car;

e) The availability of a car makes parents more likely to plan on retrieving children from school in an emergency; and

f) Parents closer to children are more likely to plan on picking up children in an emergency.

Methods

The research team, in conjunction with the Center for Neighborhood Technology (CNT), conducted over 300 in-depth structured interviews in Chicago to determine the daily practices and the arrangements that families have for picking up dependents in case of a no-notice event during the day. The sample mixed both random solicitations and snowball sampling for recruiting the study participations. Snowball sampling was pursued through CNT's institutional relationship with community-based organizations throughout the Chicago region, including work in the Logan Square community. We oversampled individuals from this community in order to get a strong representation from at least one group of parents who were connected by both culture and geography. Logan Square is a community where immigrants from both Mexico and Puerto Rico settle within the region, and it is well-served by both rail and bus. It has a neighborhood combined elementary and middle school. Our sample from Logan Square therefore included respondents who spoke only Spanish; 80 of the usable interviews were conducted exclusively in Spanish.

The concentration of respondents from one community skews the sample somewhat: we have a higher percentage of stay-at-home caregivers (SAHC), at 11 percent. The prevalence of stay-at-home caregivers in the US, according to the Bureau of Labor Statistics, runs at a little less than 10 percent. Even so, our conversations with women--particularly the Spanish-speaking stay-at-home caregivers--suggest that a simple SAHC versus employed caregiver categorization did not fit how many of these respondents, almost all women, approached their work. For many, the recession that began in the US in 2007 altered their work hours substantially, such that it was only more recently that they are both SAHCs but also on-and-off temporary workers doing cleaning, child care, or other work as it arises--but it was not arising much in the economic conditions during most of our interviews, which were conducted from July 2008 until January 2009. Among native-born mothers drawn more randomly with email, web, and newspaper solicitations from around the region, the workforce participation rate was just about at the national average of 90 percent. We oversampled mothers relative to fathers and women relative to men. Subjects who responded to recruiting materials were in general accepted until we had reached a saturation of interviews from car users and recruited at the end stage for greater representation of parents who use transit in the final sample.

Some of the native-born men in the sample were also feeling the effects of the recession, and some of our interviewees reported that they were self-employed in real estate or other small business enterprises that had had significant rollback in activity. We limited the number of unemployed men or stay-at-home fathers to only 10 percent of the sample, which is slightly less than the unemployment figures for Illinois throughout the time period.

The interviews were detailed and entailed in sum over fifty questions that could range from short-answer to more detailed, depending on the information. There were three main interviewers: two female and one male. One was the researcher in charge of the team; another was a Mexican woman; the third was an African-American male. We controlled for the interviewers as codes within the data, and there are some systematic differences in the sample by interviewer, but those can be explained by the fact that the effects pertain to the Mexican woman who conducted all the Spanish interviews--which can also be explained by variables pertaining to the Spanish-speaking respondents.

Because the interviews were structured, the variables and keywords were designated prior to the interviews and revisited once the interview pre-tests were done. Based upon the key words and phrases, interviewers took detailed notes on the answers and, working with the participants, derived dynamic mapping and routing of the respondent's answers. The maps were generated in Microsoft Streets and Trips and joined to the notes and the recording/transcription for interviews that allowed it.

Prior to the interview, respondents were given a survey questionnaire to fill out that solicited private information, such as their income, education, marital status, children, etc. These were filled out in private and sealed in an envelope so that the interviewer did not see the information. The result was a comparatively high response rate among participants for income, education, home ownership, and other sensitive topics. However, the questions were asked in a very general way: exact household income, for example, was not solicited. Instead, respondents were able to fill out whether their income was above or a below three simple threshold amounts, resulting in a categorical rather than continuous variable for income.

In addition to questions about daily activities and responsibilities, participants responded to two hypothetical daytime no-notice incident scenarios: a minor incident (Scenario #1) and a major incident (Scenario #2). In Scenario #1, an incident causing workplace and school evacuation without home evacuation (i.e., home is safe), respondents have been informed that they must evacuate their worksite immediately and stay away for the rest of the day, they have 5 minutes to leave their worksite, and their child's school must be evacuated if it is within 5 miles of the worksite. In Scenario #2, an incident causing workplace and school evacuation with home evacuation, respondents have been informed that they must evacuate their worksite immediately, their home area has also been subject to an evacuation, they have 5 minutes to leave their worksite, their child's school will be evacuated, most of the surrounding region will be evacuated as soon as possible, and they will have to be away from their home for at least three days. For both scenarios, participants were asked about their planned destinations, modes of travel, intermediate stops for gathering others, and whether they anticipated being gathered themselves.

Data Descriptive Statistics

Definitions of the selected variables, both explanatory variables and decision-making variables, and their descriptive statistics are displayed in Table 3.1. Some responses are incomplete because respondents were not willing to reply to certain questions. In the dataset, 74% of respondents are parents of children under 18 years old; 68% of respondents are women; 69% are currently married; 11% of the respondents are SAHCs; 37% are Caucasians, 38% are Hispanics (including Mexican, Central American, Puerto Rican, South American, Latino and Mexican American), 16% are African Americans, and 8% are Asians and Pacific Islanders; 70% of respondents have a personal car to use. According to U.S. Census Bureau (2009), for Chicago, Illinois, 26.8% of households have children under 18 years old; 33.2% are married-couple families; 41.9% are White, 34% are Black or African American, and 4.9% are Asians; 27.4% are Hispanic or Latino. Compared with Census data, the interviews oversampled parents and married couples; this oversampling was intentional for the purpose of investigating household pick-up and gathering behavior. Minorities were also oversampled for the reasons discussed above.

Table 3.1. Variable Definitions and Descriptive Statistics

Variables	Sample size	Mean
Respondent:		
Parent (parent of a child under the age of 18 =1)	315	0.74
Gender (female = 1)	315	0.68
Age 18-35 (yes =1, no = 0)	313	0.42
Age 36-55 (yes =1, no = 0)	313	0.48
Age 56-75 (yes =1, no = 0)	313	0.08
Age >75 (yes =1, no = 0)	313	0.02
Ethnicity (Caucasian =1)	315	0.37
SAHC (stay-at-home caregiver =1)	315	0.11
Marital status (currently married = 1)	315	0.69
Education (college or above =1)	312	0.65
Driver (respondent can drive a car = 1)	314	0.88
Employment (employed or volunteers = 1)	314	0.88
Car availability (personally having a car to use = 1)	314	0.70
Commute mode (driving to leave work =1)	282	0.57
Household:		
Household income (exceeding $50,000 per year = 1)	308	0.54
Number of adults in the household	315	2.09
Number of children under the age of 18 in the household	315	1.50
Number of cars in the household	315	1.38
Having a child within 5 miles of the worksite (yes=1)	194	0.50
Spouse:		
Spouse education (college or above =1)	206	0.38

Spouse commute mode (driving to work =1)	195	0.64
Trip:		
Pick-up distance in normal situations (miles)	188	7.23
Pick-up distance in Scenario #1 (miles)	90	2.23
Pick-up distance in Scenario #2 (miles)	187	6.29
Travel distance from spouse to children in normal situations (miles)*	103	9.44
Travel distance from spouse to children in Scenario #1 (miles)*	43	9.42
Travel distance from spouse to children in Scenario #2 (miles)*	103	9.18
Travel distance from the respondent's workplace to home (miles)	242	8.35
Travel distance from the respondent's workplace to spouse's workplace (miles)	130	9.55
Dependent variables:		
Pick up a child on a normal afternoon (yes=1)	233	0.48
Pick up a child for Scenario #1 (yes=1)	99	0.74
Pick up a child for Scenario #2 (yes=1)	233	0.57

Note: the statistics for commute mode is for the sub-dataset of employed respondents; the statistics for spouse education and decisions of gathering a spouse is for the sub-dataset of married respondents; the statistics for spouse commute mode is for the subset where the respondent's spouse is employed; the statistics for decisions of picking up a child on a normal afternoon and in Scenario #2 is for the sub-dataset where the respondent is a parent of a child under 18, and the sub-dataset for Scenario #1 is where the respondent is a parent of a child under 18 and the child most likely to be picked up is within 5 miles of the respondent's location.
* Distances are measured to the most likely child to be picked up - defined based on the respondent. This child may vary across scenarios.

Concerning child-serving travel, 48% of parents chauffeur a child on a normal weekday and 57% of parents do so in Scenario #2. For Scenario #1, the overall percentage of parents picking up a child is 47%, while 74% of parents who have children within five miles of the worksite report picking up a child, and only 23% do so if the children are more than five miles away from parent's worksite. With a five-mile evacuation radius for Scenario #1, the numbers here indicated that parents are more likely to pick up a child in emergency situations than on a normal weekday.

For those respondents with multiple children in the household, one child is chosen to investigate the respondent's behavior towards this child, based on (1) if the respondent conducts child pick-ups, the first child who he/she would pick up is selected and (2) if the respondent does not pick up any child, the child closest to the respondent during the daytime is selected. This child is termed as *"the child most likely to be picked up"* in the paper, and all child-related factors are associated with this child. *Pick-up distance* refers to travel distance of a trip that a parent conducts to gather *the child most likely to be picked up*.

As shown in Table 3.1, the average pick-up distance is 7.23 miles in normal situations, 2.23 miles for Scenario #1, and 6.29 miles for Scenario #2; average work distance for the respondent is 8.35 miles. Average distance from the respondent's workplace to his/her spouse's workplace is 9.55 miles. The data also showed that average work distance is 7.0 miles for women, and 10.87 miles for men, which confirms hypothesis (c) - working women are closer to the child and home locations than men are. Figure 3.1 illustrates the distributions of pick-up distance and distance between a respondent and spouse; in general, the longer these distances are, the lower the frequencies are.
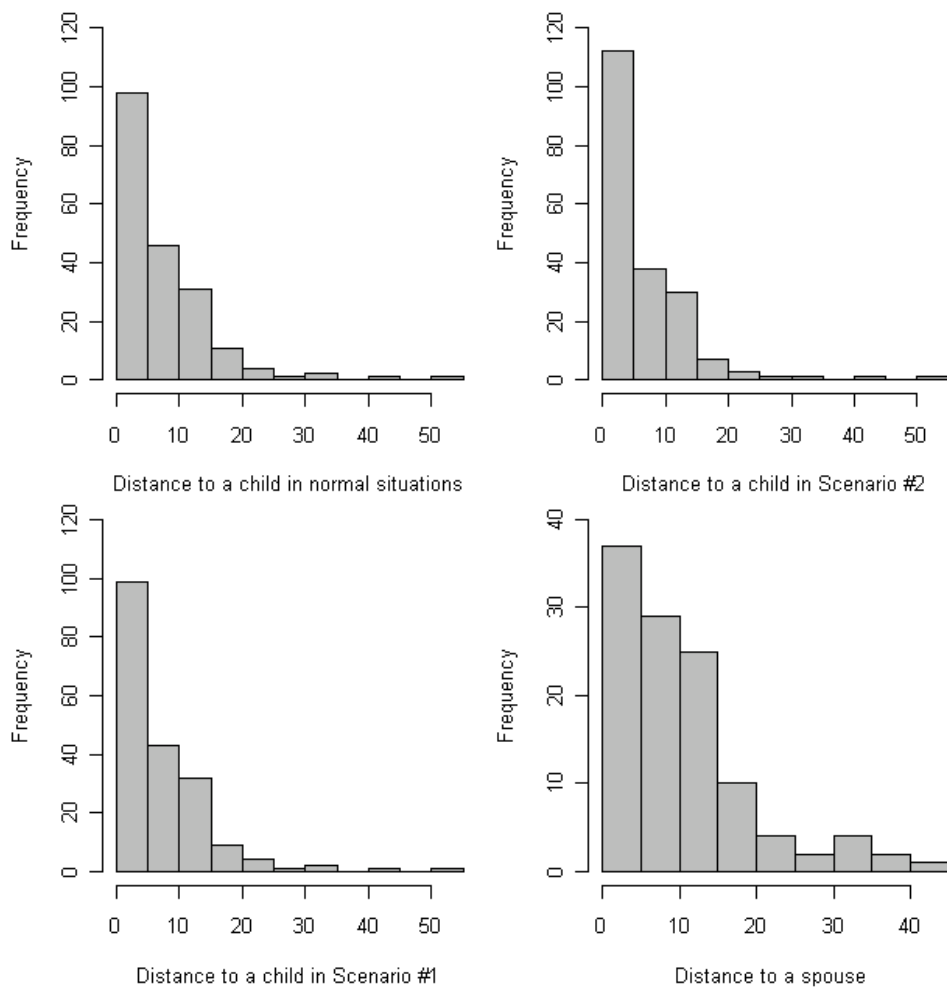

Figure 3.1. Distributions of Respondent's Distance to a Child and Spouse

Results and Discussion

Interview Themes

In this section, we discuss some of the more impressionistic results from the interviews. Many of the nuanced comments from working parents do not come through in the models, and some of the comments reveal really interesting things about how women view child-related travel.

In our sample, women are 10.6 times more likely to report that they pick up children from school than male parents, in dual parent households with children outside the home. However, class, ethnicity, and proximity to the school qualitatively affected these outcomes and how women understood their roles, as low-income women, even those who are stay-at-home mothers, were somewhat less likely to drop off and pick up their children at school than were relatively high-income working women. This finding reflects two important splits by class, ethnicity, and neighborhood in the comments. The first split concerns place-based resources upon which the women from the oversampled neighborhood, Logan Square, both constructed and consumed. Within Logan Square, children were much more likely to walk to school than to be driven. With the close spatial area surrounding the school, mothers there reported multiple, usually female, adult caregivers ranging from extended family to "neighborhood aunties"--unrelated women neighbors--who routinely volunteered at the elementary school on different days and who took responsibility for walking with all the children within a block or within an apartment complex. These mothers, predominately full-time home caregivers, reported that they took their turns with walking children, on and off, according to the need for child supervision as it arose on a day-to-day basis.

A second group of comparatively low-income mothers contrasted with mothers from the Logan Square community and from the relatively high-income, mostly professional mothers in the data set. This second group is primarily lower-income women spread throughout the Chicago region. They tended to be single parents and relatively young. These low-income mothers, like those in Logan Square, were less likely to transport children to school than higher-income women. However, this difference derived not from having neighborhood resources, but from low-income women's relative disadvantage in altering work hours. This group of women is usually at work, first shift or second shift, or in classes themselves and thus had no flexibility to alter their schedules for children's schedules. This subset of women, from a mix of ethnic

backgrounds, often lived with or next to parents who took on responsibility for gathering children at school and other activities.

The differences between these three groups of female caregivers challenge our conventional wisdom in travel demand somewhat. The fact that higher income women are so much more likely to gather children can be interpreted within households as a measure of inequality between male and female caregivers, but it also reflects at least some level of class privilege in their ability to exercise control over their work and schedules that prevents other women, such as those working inflexible hours, from--if the interviews are to be believed--doing caring work that many of these women valued highly, such as spending time before and after school walking with their children. For the Logan Square group, the lower likelihood of child transport does not necessarily reflect hardship in the same way. The work surrounding children's mobility was shared in a well-resourced neighborhood environment, with elementary and middle schools within walking proximity, extended family networks, and friendships within the homogenous, Spanish-speaking residents of the neighborhood. Doing more or less with child transport can mean any number of things--both positive and less so--within the spectrum of gender, ethnicity, and class structures in cities.

Another effect noted during the interviews reflected the difference in transport care work between child care and elder care. The sample included a small number of those who cared for dependent elders, disabled adult children, or spouses. This type of caring work tends to rank much lower in terms of personal gratification than caring work related to children (Coltrane 2001). This sentiment was strongly reflected in the responses reported from these participants. Unlike the community involvement around children demonstrated in Logan Square or the "shared time" spent commuting to school reported by relatively affluent mothers, respondents who transported dependent elders and adults reported that this type of transport work was lonely, full of effort, and occurred with little support other than the occasional well-meaning neighbor, adult child they hesitated to ask, and church members. Elderly, comparatively frail women caring for their spouses in worse health reported particularly difficult struggles with mobility. The respondents caring for dependent adults, primarily women, related choices and constraints largely invisible in the research discussion about gender that attributes women's travel for care

as centering on children. This is a gap in the travel behavior research, where only a few studies have attempted to examine these issues.

When asked about emergency pick-ups, where children had to be removed from school with no notice, the gender disparities lessened. For these types of situations, male respondents were somewhat more likely to respond that they would gather their child than on a normal day (these results are revealed through the logistic regression models discussed further below). Respondents who had done little emergency pre-planning--the majority--reported that they would try to coordinate these types of pick-ups via cell phone first. The results from the models and interviews show that parents generally believed that mode mattered: in two-caregiver households with transit and car commuters, the person who had the car was more likely to gather the child in case of an emergency, even if on a normal day, the child was picked up by a transit-community caregiver. Distance between workplace and home mattered more for emergency runs than for everyday travel. In keeping with previous results, however, the female caregiver in the partnered households worked at locations closer to the child's daytime location than the male partner. For the small number of individuals interviewed belonging to same-sex couples with children (six), split care-related transport according to job flexibility, varied from morning to evening commute, was coordinated on a daily basis according to schedules via cell phones.

Statistical Modeling

In the dataset, only 0.3% of child pick-up activities were conducted by the respondents who are not parents (e.g., grandparents, neighbors, etc.); this small probability event was not taken into consideration in the logistic modeling, which was based on the sub dataset where respondents are parents of a child under the age of 18.

The statistical analysis for Scenario #1 examined the parents who have children within 5 miles of the worksite. In Scenario #1, the evacuation radius is 5 miles around respondents' worksites, and children within this 5 mile radius must be evacuated. In the dataset, 99 interviewed parents have a child located within 5 miles of their workplaces, and 73 (74%) of them anticipated picking up the child; while, among 93 interviewed parents whose children are over 5 miles away, only 21 (23%) reported picking them up.

Influencing Factors

Informed by previous studies (Baker 1991; Gladwin and Peacock 1997), the following factors were examined for potential influence on child-chauffeuring behavior: gender, age, ethnicity, education, stay-at-home caregiver status, household income, car availability, possession of a driver's license, number of adults in the household, number of cars in the household, number of children under 18 in the household, and travel distance from a respondent's workplace to a child's location) by conducting Chi-square analyses for the binary or category variables and conducting logistic regressions with one explanatory variable for continuous variables. A Chi-square test allows testing the association between two binary or category variables, i.e., the row and column variables in a two-way table; the results of Chi-square analyses are shown in Table 3.2.

Table 3.2. Associations between Child-Chauffeuring Behavior and Influencing Factors

Factors	Controlling conditions	Values	A normal weekday			Incident Scenario #1			Incident Scenario #2		
			Yes	No	Chi-square (odds ratio)	Yes	No	Chi-square (odds ratio)	Yes	No	Chi-square (odds ratio)
Gender	-	Female	102	63	45.6***	67	16	12.9***	115	51	37.5***
		Male	9	59	(10.6)	6	10	(6.98)	17	50	(6.63)
Household income	-	Exceeding $50,000 per year	70	62	5.1**	45	16	0.03 n.s.	83	49	6.9***
		Not exceeding $50,000 per year	36	59	(1.85)	26	10	(1.08)	43	52	(2.05)
Ethnicity	-	Caucasian	41	26	6.9***	26	5	2.39 n.s.	49	19	9.28***
		Non-Caucasian	70	96	(2.16)	47	21	(2.32)	83	82	(2.55)
Driver	-	Yes	95	106	0.20 n.s.	57	25	4.04*	115	86	0.34 n.s.
		No	16	15	(0.84)	15	1	(0.04)	16	15	(1.25)
Car availability	*Pick-up distance <= 5mi*	Having a personal car to use	45	21	0.14 n.s.	46	19	3.87**	53	18	3.76*
		Without a personal car to use	16	9	(1.21)	20	5	(0.61)	19	15	(2.32)
	Pick-up distance > 5mi	Having a personal car to use	31	44	3.95**				39	31	3.87**
		Without a personal car to use	4	18	(3.17)		-		3	9	(3.77)
Commute mode	*Respondents are employed, and pick-up distance <= 5mi*	Driving to leave work	30	14	0.05 n.s.	28	15	1.87 n.s.	35	13	0.77 n.s.
		Leaving work by other modes	31	16	(1.11)	38	9	(0.44)	37	20	(1.46)
	Respondents are employed, and pick-up distance > 5mi	Driving to leave work	27	37	3.04*				33	26	1.87 n.s.
		Leaving work by other modes	8	25	(2.28)		-		9	14	(1.97)
Stay-at-home caregiver	-	Yes	25	8	12.2***	23	2	5.76**	29	4	15.2***
		No	86	114	(4.14)	50	24	(5.52)	103	97	(6.83)
Age	-	18-35	47	48	0.34 n.s.	34	11	0.19 n.s.	56	39	0.47 n.s.
		>35	62	74	(1.17)	38	15	(1.22)	74	62	(1.20)
Education	-	Having a college degree	75	69	2.5 n.s.	48	15	0.54 n.s.	90	54	4.48**
		No college degree	36	51	(1.54)	25	11	(1.41)	42	45	(1.76)
Employment	-	Employed or volunteers	92	116	9.03***	59	24	1.86 n.s.	112	96	6.21**
		Unemployed (not a volunteer)	19	6	(0.25)	14	2	(0.35)	20	9	(0.29)

*** $p<.01$; ** $p<.05$; * $p<=.10$; n.s. $p>0.1$;

The statistics for all variables in Scenario #1 is for the sub-dataset that parents have children within 5 miles of the worksite.

Chi-squared approximation may be incorrect when there are expected values less than 5; in that case, the p-value is computed using Monte Carlo methods (Hope, 1968) with 2000 replicates.

Gender is significantly related to picking up children in normal and emergency situations; this finding is consistent with previous work that suggests gender is the most important factor in determining child-serving stops during the journey to work among all social, demographic, or economic factors (Mauch and Taylor 1997; Coltrane 2000; Rosenbloom and Burns 1993). As shown in Table 3.2, the odds of picking up a child for women are 10.6 times the odds for men on a normal day (supporting hypothesis a), 6.98 for Scenario #1, and 6.63 for Scenario #2. The odds ratios also showed that gender difference in child-related travel behavior lessens under emergency conditions compared to normal situations: more fathers plan to gather their children than on a normal workday. Among 165 interviewed mothers, 102 (62%) are responsible for picking up a child on a normal weekday, and 115 (70%) do so in Scenario #2; among 68 fathers, only 9 (13%) report picking up a child on a normal day, and 17 (25%) do so in Scenario #2. For Scenario #1, among 83 mothers and 16 fathers who have children within 5 miles of the worksite, 81% of females (67/83=81%) and 38% of males (6/16=38%) report picking up a child. Both women and men are more likely to pick up a child under emergency situations than they are on a normal day. The interviews revealed that men's participation in child-related travel increases for emergency situations; however, it is still low compared to women, which implies that gender difference in child-related travel still exists and is apparent in an emergency, that is, in cases of evacuation, parents respond according to their everyday roles with regard to transport-related care work. Therefore the findings here also support *hypothesis b.*

Ethnicity

Ethnicity (Caucasian vs. non-Caucasian) is significantly associated with the decision of picking up children from school on a normal day and for Scenario #2 (the odds ratio is 2.16 at the $p<.01$ level for the normal situation and 2.55 at the $p<.01$ level for Scenario #2), which supported Mauch and Taylor's (1997) finding that child-serving trips are related to race or ethnicity. The predicted odds revealed that Caucasians are more likely to retrieve a child from school than non-Caucasians are.

Previous studies argued that household financial status is behind ethnic difference in transport-related decisions: Mauch and Taylor (1997) concluded that effects of ethnicity on child-serving travel can be explained by economic status rather than ethnicity itself; Gladwin and

Peacock (1997) indicated that lower propensity for ethnicity minorities to evacuate from hurricanes is a result of economic conditions rather than race or ethnicity itself because of their limited evacuation options. In order to better understand why ethnicity minorities are less likely to chauffeur children from school, we examined a series of logistic regression models of ethnicity and one other variable. We found that ethnicity is no longer significant once income is added but remained significant when other variables (car availability, number of adults, commute mode or parents/in-laws living in the home) were added. Household income connects virtually all these variables, and it enables a higher likelihood of child-serving travel among Caucasians, substantiating Mauch and Taylor's and Gladwin and Peacock's conclusions. In other words, given the same household income, Caucasians and non-Caucasians may make the same decision on picking up children from school. This finding can be explained by high correlation (0.43) between ethnicity and income.

The odds ratios showed that ethnic disparity in child-related travel behavior increases for emergency Scenario #2 compared to normal situations, which implies that ethnic minorities suffer more barriers to emergency travel than Caucasians. As for gender-ethnicity combination effects, it was found that there is no significant difference in child-related travel between Caucasian men and non-Caucasian men, which reflects that, as the secondary child caregivers, men make decisions less constrained by ethnicity or the correlated household financial status.

Household income

Table 3.2 showed that household income has significant positive associations with child-chauffeuring behavior on a normal day and under Scenario #2; however, it was not significant for Scenario #1. On a normal weekday, the predicted odds of picking up a child for parents with household income exceeding $50,000 per year are 1.85 times the odds for those whose income was lower than $50,000. The odds ratio revealed that high-income parents are more likely to pick up a child from school than low-income parents on a normal afternoon; the possible reasons have been discussed earlier: 1) low-income mothers may work inflexible hours, are not able to alter their schedules to their children's schedules, and they may live with or near extended family members who can assist with child responsibilities; 2) mothers, living within some low-income communities where schools are within a short walking distance, share responsibility of walking children to school with their friends in the neighborhood. Another potential reason is that as

household income is highly correlated with car availability (0.42), higher-income parents are less mobility constrained than low-income parents, and mobility affects picking up a child from school (this will be discussed in detail later).

Household income appears not to be significantly related to the activity of retrieving a child from school for Scenario #1, which is a result of the Scenario #1 definition – only schools within 5 miles of the worksite need to be evacuated. By running an additional Chi-square test for those having a child within 5 miles of the worksite for normal situations, we found there are no significant associations between income and child pickup activities. That is, when controlling for pick-up distance less than 5 miles, household income is not significant to child-related travel, possibly because when parents are close to their children, there are fewer limitations or constraints for low-income people to pick up children from school; for example, the workplace must be evacuated and schedule issues disappear. This reason can also explain a lack of significant effects of ethnicity for Scenario #1.

For Scenario #2 (the large-scale emergency), the predicted odds of picking up a child for parents with household incomes exceeding $50,000 per year are 2.05 times the odds for those whose income is lower than $50,000; the odds ratio is higher than 1.85 on a normal afternoon. Concerning child-related travel behavior, income disparity still exists under emergency conditions and increases compared to normal situations, probably because high-income parents are less constrained with mobility than low-income parents (household income is highly correlated with car availability with the correlation coefficient of 0.42), and mobility matters, as discussed previously.

Car availability

Of parents who have a personal car to use, 50% would pick up a child on a normal day; 70% and 62% would do so in Scenarios #1 and #2, respectively (36% of parents have more than one car in the household). Based on the Chi-square test, car availability is not significantly associated with child pick up behavior on a normal day; however, when controlling for pick-up distance greater than 5 miles, car availability becomes significant: the predicted odds for those having a personal car to use are 3.17 times the odds for those who do not have access to a car. The effects of car availability on child-chauffeuring behavior in normal situations are constrained by the distance

between them; when parents are farther than 5 miles from children, parents who drive are more likely to pick up children on a normal day than those taking transit or other modes; when they are not far away from each other (within 5 miles), there is no significant difference whether parents drive or take transit. The finding also implies that distance is more important to child-serving travel behavior than car availability: parents who work close to their children's schools and take transit are more likely to chauffeur them than those who drive but work far away.

Car availability is significant to picking up children from school in cases of emergencies and the significance is not affected by pick-up distance, which is different from normal situations and suggests that even though parents are not far away from children, having a car to use makes a significant difference for child pick-up behavior in an emergency. The finding was supported by the interview analysis addressing whether transport modes matter in cases of emergencies: the parent who had the car is more likely to pick up the child in case of an emergency, even if the child was normally picked up by a transit-commuting caregiver. It was also consistent with previous conclusions: automobile commuters are more likely to chain activities than transit users (Kumar and Levinson 1995).

Commute Mode

Although respondents may have the ability to drive and a car available for them to use, they may choose to commute by a different means. The variable "commute mode" specifically captures whether the respondent plans to leave work by driving or some other mode. "Commute mode" is strongly correlated with car availability (correlation coefficient of 0.68 for employed respondents in the dataset) and shows similar patterns with car availability pertaining to child-related travel behavior in normal situations. Specifically, both of these variables are not significant factors when pick-up distance is less than 5 miles, and become significant when distance is greater than 5 miles, and the significance of commute mode is only slightly lower than car availability (the Chi-square statistic is 3.04 for commute mode and 3.95 for car availability). In both emergency scenarios, commute mode becomes insignificant to child-serving behavior, while car availability is significant. This finding implies that when determining whether to pick up children, parents consider their transportation modes to/from work and car availability on a normal day; however, in an emergency, parents' plans rely on whether they have access to a car rather than their normal commute mode. The finding reflects people seeking balance between work and family duties in

normal situations, while, under emergency conditions, parents make their evacuation decisions based on all resources they have access to.

Stay-at-home caregiver

Being a stay-at-home caregiver, disproportionately a female role in this sample, is significantly associated with child-chauffeuring decisions. The predicted odds of picking up children for stay-at-home caregivers are 4.1 times the odds for working caregivers for normal situations, and 5.5 and 6.8 times for Scenarios #1 and #2, respectively. Thus, stay-at-home caregivers are more likely to pick up their child than working caregivers, which makes sense as child-care is a primary job of stay-at-home caregivers while those employed outside the home have to balance employer and family tasks and schedules. Compared to their characterization of a normal day, the difference between stay-at-home and employed caregivers increases under emergencies. Of stay-at-home caregivers, 92% and 88% reported picking up a child for emergency Scenario #1 and #2; the high propensity reflects that their time schedules are often quite flexible, and they are less constrained by distance (between parents and children) than employed caregivers. Stay-at-home caregivers tend to be geographically proximate to their children; in the dataset, the average distance between them is 1.8 miles, and the nearer the parent is to the child, the more likely he/she picks up the child (proved later). In these shorter distances, child-related travel behavior is not significantly affected by car availability.

Travel distance (Pick-up distance from a parent to the child most likely be picked up)

To examine whether continuous variables (e.g., travel distance from a respondent and a child, distance from a spouse and a child, number of adults in the household, number of cars in the household and number of children under the age of 18 in the household) significantly affect child-chauffeuring activity without controlling for other variables (the Chi-square analysis is not valid for continuous variables), logistic regression models with these factors as the sole explanatory variable were constructed, and the odds ratios are shown in Table 3.3.

Table 3.3. Odds Ratios for Child-Chauffeuring Propensity

	A typical weekday		Incident Scenario #1		Incident Scenario #2	
	Odds Ratio	Significance	Odds Ratio	Significance	Odds Ratio	Significance
Pick-up distance	0.88	***	0.50	***	0.94	**
Number of adults in the household	0.59	*	0.77	n.s.	0.62	**
Number of cars in the household	1.17	n.s.	0.67	*	1.16	n.s.
Number of children under the age of 18 in the household	0.95	n.s.	0.87	n.s.	1.08	n.s.

*** $p<0.01$; ** $p<0.05$; * $p<0.10$; n.s. $p>0.1$.

Pick-up distance had significant negative effects on the parent's decision to pick up the child at the $p<.01$ level in all three situations; a 1-mile increase in distance decreases the odds of picking up a child by 12% on a normal weekday, by 50% for Scenario #1 (with the threshold of 5 miles) and by 6% for Scenario #2. The farther a parent is away from a child, the less likely he/she is to chauffeur the child from school. In an emergency, the difference in child-related travel behavior by pick-up distance lessened, that is, distance still matters but not as much as in normal situations; this reflects that some parents who work far away from children and do not chauffeur them on a normal day may plan to pick them up if a disaster occurs.

In order to test how the spouse's distance to children would affect the respondent's child-related travel behavior, spouse's distance was added to the models as another explanatory variable. With the spouse's distance included, a 1-mile increase in respondents' pick-up distance decreases the odds of picking up a child by 12% on a normal day and by 5% for Scenario #2; while, with respondents' pick-up distance controlled, a 1-mile increase in spouse's distance to children increases the odds of picking up a child by 6% on a normal day and by 7% for Scenario #2; a 1-mile increase in both respondent's distance and spouse's distance decreases the odds of the respondent's picking up a child by 7% on a normal day, and slightly increases the odds by 1.4% for Scenario #2. This reflects that the location of one's workplace affects his/her spouse's child-chauffeuring behavior: the farther a parent is from a child, the more likely his/her spouse is to pick up the child from school. Under normal situations, one's decisions are more affected by locations of his/her workplace than by his/her spouses' location, and, under an emergency, both locations have effects on respondents' plan formulation around child-serving travel decision to the same extent. This finding occurs possibly because parents can arrange for other people to

chauffeur children on a normal day, while, in cases of emergency, they do not plan on the assumption that the other caregiver—or even trusted friends—will do the pick-ups.

Pick-up distance is strongly correlated with work distance (the correlation coefficient is 0.835 for a normal day and 0.735 for Scenario #2); work distance is significantly correlated with car availability (0.194). With controlling for having a personal car available, pick-up distance is significant at the $p<.01$ level; a 1-mile increase in the pick-up distance decreases the predicted odds of picking up a child by 10% on a normal day and by 7% for Scenario #2. When a personal car is not available, the pick-up distance is also significant, and a 1-mile increase in the distance decreases the predicted odds of picking up a child by 22% on a normal day and by 15% for Scenario #2. This indicates that when making decisions of whether or not to pick up a child, parents who have a personal car to use are less affected by distance than others; the reason could be that people perceive lower travel time for a long-distance trip by driving than by public transit, and personal vehicle travel is considered less onerous.

Pick-up distance is strongly correlated with gender (the correlation coefficient is 0.37 for normal situations and 0.18 for Scenario #2). With controlling for mothers, the distance is significantly associated with child-serving travel behavior, and a 1-mile increase in the distance decreases the predicted odds of picking up a child by 10% for normal situations and 13% for Scenario #2; when controlling for fathers, the distance is no longer significant. So, women tend to be affected by distance when they make decisions on picking up children from school, but men do not, which could either be a real reflection of men conquering difficulties of long distance if they choose to retrieve children, if the sample adequately captures the number of men handling child-serving trips. It may be that the emphasis on capturing transit commuters and lower-income urban residents undersampled men who undertake child-serving travel (e.g., only 11 interviewed fathers reported picking up a child on a normal day, and 19 did for Scenario #2) and therefore was not able to reveal the underlying relationships.

Other Variables

The statistics showed that age of parents and whether parents can drive a car were not significantly related to retrieving children from school for all three situations, which is reasonable since parents' care responsibility for children depends on their status of being a parent,

regardless of their age and capacity to drive. Education level, as highly correlated with household income with the correlation coefficient of 0.57, showed similar patterns with household income. As stay-at-home caregivers in the dataset do not include male caregivers, employment status of respondents (allowing stay-at-home caregivers to volunteer) was also investigated, and its significance for child pick-up behavior in the three situations follows similar patterns with stay-at-home caregivers.

The number of adults residing in the home is marginally significant to the decisions on a normal weekday and Scenario #2, and one more adult living in the household decreases the odds of picking up a child by 27% (1-0.73=0.27); this suggests that other adults in the household could help with picking up children from school. The number of cars in the household and number of children under 18 did not significantly affect child-chauffeuring in all three situations.

Logistic Regression Results
Three preferred logistic regression models were developed to predict the probability that parents retrieve their children from school in three situations: a normal weekday and two incident scenarios, as shown in Table 3.4. These models were obtained after testing all potentially significant variables and interaction terms in R. The models were based on the sub-dataset where the respondents are parents with at least one child staying with neither of the parents during the daytime; in other words, in the sub-dataset, the respondents are parents in need of picking up children in an emergency.

Table 3.4. Logistic Regression Models to Predict the Probability that Parents Pick up a Child from School

	Normal weekday		Incident Scenario #1		Incident Scenario #2	
	Estimate	Wald Chi-Square	Estimate	Wald Chi-Square	Estimate	Wald Chi-Square
Intercept	2.5976		-1.2783		3.2988	
Gender (male vs. female)	-2.1006	18.8[***]	-0.9176	4.6[**]	-3.2036	29.6[***]
Pick-up distance	-.0652	3.8[*]			-0.1354	9.2[***]
Household income	.9259	6.3[**]			0.9744	6.2[**]
Employed	-2.3414	4.7[**]			-2.0613	3.5[*]
Gender * Pick-up distance					0.1469	7.5[***]
Caucasian			0.8246	3.9[**]		
Stay at home caregiver			2.6698	6.3**		
Having a child in the impacted area			1.8395	22.7[***]		
Sample Size	183		178		182	
Likelihood Ratio Chi-square	63.02[***]		74.28[***]		66.68[***]	
McFadden's R^2	0.2484		0.3017		0.272	
AUC	0.808		0.838		0.834	
Correct Rate (%)	77.6		78.7		78	

[***] $p<.01$; [**] $p<.05$; [*] $p<.1$.
Correct rates are corresponding to the probability level of 50%.

All three presented models passed the Chi-square test at the p<0.01 level, which indicated excellent goodness of fit. However, excellent goodness of fit does not necessarily guarantee excellent explanatory power - how well a model accounts for the causes of the fact we explore (in this study, how well the models can reflect the reasons behind a parent's decision of picking up a child from school). Here AUC, area under the Receiver Operating Characteristic (ROC) curve, was used to measure the models' discrimination capacity. All three presented models have AUC higher than 0.8, which indicated that the models have excellent discrimination capacity according to Hosmer and Lemeshow (2000).

The prediction accuracy can also be measured by correct rates. In the context of the study, a correct rate is the proportion of respondents whose decisions of picking up a child are correctly predicted. A cut-off probability is introduced to determine which outcome is obtained: if the predicted probability is higher than the threshold, then this respondent is predicted to pick up a child (in this study, 0.5 was selected as the cut-off point to measure models' prediction capacity). From Table 3.4, 77.6% of respondents' child-pick-up decisions were correctly predicted for a normal situation, and this value is 78.7% and 78% for incident scenarios #1 and 2, indicating that the prediction accuracy of three models is satisfactory. Furthermore, for Scenario #2, correct rates are 73-76% while the cut-off probability ranges from 0.3-0.7; when the cut-off probability

ranges from 0.1-0.8, correct rates are above 60%; outside the range 0.1-0.8, correct rates drop under 60%. Overall accuracy is not sensitive to the cut-off probability when it is in a certain range (0.3-0.7 for this dataset).

Based on the regression results, on a normal weekday, car availability was not significant to predicting the probability that parents chauffeur a child from school even given that distance is included in the model. Effects of ethnicity on child-chauffeuring travel behavior diminish (even become not significant) given that household income is included in the model. Thus, household income, instead of car availability and ethnicity, is included in the model. As shown in Table 3.4, on a normal weekday, the predicted odds of picking up a child for women are 8.2 (1/exp(-2.1006)=8.2) times the odds for men; a 1-mile increase in pick-up distance decreases the odds of picking up a child by 6.3% (exp(-.0652)-1=-.063); the predicted odds of picking up a child for those whose household income exceeds $50,000 per year are 2.52 (exp(.9259) = 2.52) times the odds for others; the predicted odds of picking up a child for those who are unemployed and not volunteers are 10.3 (1/exp(-2.3414)=10.3) times the odds for others. Interaction effects of gender and ethnicity, gender and pick-up distance, gender and car availability, and car availability and pick-up distance were not statistically significant.

As shown in Table 3.4, the model for Scenario #1 includes four explanatory variables, i.e., gender, ethnicity, stay-at-home caregivers, and a dummy variable – having a child in the impacted area (within 5 miles of the worksite for this scenario), all significant at the 0.05 level. Because employment status causes quasi-complete separations of the dependent variable, stay-at-home caregiver is selected as an explanatory variable instead. In this scenario, the predicted odds of picking up a child for parents having a child in the impacted area are 6.3 (exp(1.8395)=6.3) times the odds for those who do not; the predicted odds of picking up a child for women are 2.5 (1/exp(-.9176)=2.5) times the odds for men; the predicted odds of picking up a child for Caucasians are 2.3 (exp(.8246)=2.3) times the odds for non-Caucasians; the predicted odds of picking up a child for stay-at-home caregivers are 14.4 (exp(2.6698)=14.4) times the odds for others. Not surprisingly, the dummy variable was the most important factor in determining whether parents would pick up children or not.

The model for Scenario #2 includes four explanatory variables, i.e. gender, pick-up distance, employment status and household income, and the interaction of gender and distance,

all significant at the 0.10 level. In this scenario, the predicted odds of picking up a child for those with household income exceeding $50,000 per year are 2.65 (exp(.9744)=2.65) times the odds for those with household income lower than $50,000 per year; the predicted odds of picking up a child for unemployed parents are 7.9 (1/exp(-2.0613)=7.9) times the odds for employed parents. A 1-mile increase in pick-up distance decreases the odds of picking up a child by 12.7% (exp(-.1354)-1=-.127) for mothers and increases the odds of picking up a child for fathers by 1.16% (exp(-.1354+.1469)-1=.0116); increasing pick-up distance dramatically decreases the probability that mothers pick up a child.

Car availability is no longer significant given that household income is included in the model. When controlling for household income exceeding $50,000 per year, 65% of respondents who have access to private cars reported picking up children for Scenario #2, and so did 50% of respondents who do not have access to personal cars; when controlling for household income lower than $50,000 per year, the numbers become 50% and 41%. Regardless of car availability, low-income respondents are less likely to pick up a child than high-income respondents. This implies that low-income households are constrained by other factors besides their accessibility to personal cars to conduct child pick-up behavior in an emergency.

Figure 3.2 illustrates the predicted probability that parents pick up a child based on the regression results with controlling for respondents being employed or volunteers. Figure 3.2 (a) clearly illustrates that pick-up distance affects the probability that fathers pick up a child on a normal weekday; however, it does not significantly affect the probability under emergency situations. Figure 3.2 (b) shows that the probability of mothers picking up a child decreases dramatically with increases of travel distance between them in normal and emergency situations. For both mothers and fathers, in most cases, the probabilities of picking up children are higher under Scenario #2 than normal situations, as illustrated in Figure 3.2. Figure 3.2 (b) also illustrates that mothers' decisions of picking up a child are affected by distance to greater extents in an emergency than in normal situations. When parents and children are 5 miles away and household income is higher than $50,000 per year, the probability that fathers pick up a child are 22% on a normal weekday and 38% for Scenario #2, and the probability that mothers pick up a child are 70% on a normal weekday and 82% for Scenario #2. Figure 3.2 also illustrates that

parents who have a larger income are more likely to pick up a child from school under both normal and emergency situations.

Fathers

(a)

Mothers
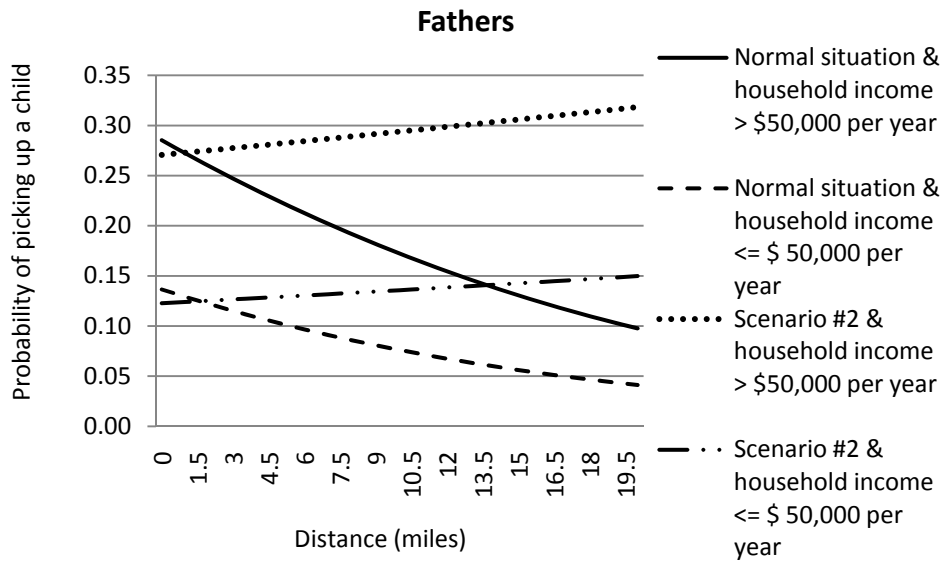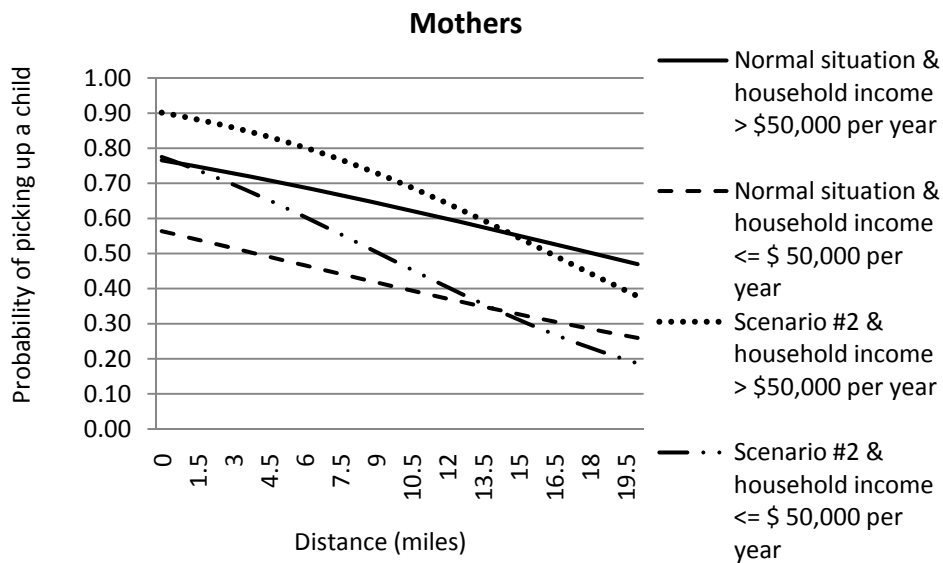
(b)

Figure 3.2. Predicted Probability that Employed/Volunteer Parents Pick up a Child from School

Compared with the observations, the regression models over-predict the number of women who would pick up a child in emergencies, and under-predict for men. For instance, for

Scenario #2, a total of 182 observations with complete information were selected to build the model to predict child-chauffeuring propensity, in which 128 are women and 54 are men. Among 128 mothers, 96 reported picking up a child from school, while 115 were predicted to do so with a cutoff probability of 0.5; among 54 fathers, 13 reported picking up a child, while 2 were predicted to do so with a 0.5 cutoff probability. Lower cutoff values further over-predict the number of mothers picking up a child and the improvement for fathers was slight. The underprediction for fathers could be an artifact of the smaller number of men reporting pickups in the dataset.

Conclusions and Policy Implications

This manuscript is among the first to present predictive models of emergency family gathering for evacuation purposes. Based on 315 interviews conducted in the Chicago metropolitan area, we developed logistic regression models to predict the propensity of gathering a child. We examined child gathering in the context of a normal day, small evacuation, and larger evacuation. Furthermore, this paper fills a gap in our knowledge about how families allocate the caring work that includes mobility, such as picking up and dropping off children at school.

The key findings of this study are summarized below:

- Women are more responsible for picking up children from school than men in both normal and evacuation conditions, be they mothers or female members of extended family networks. This finding supports the large body of literature addressing gender differences in care work and transportation activities.
- Even though, in an emergency, parents largely respond according to their everyday roles with regard to transport-related care work, both mothers and fathers are more likely to gather their children from school. Thus, in an evacuation, parents are more likely to gather their own children rather than allow the children to take a school bus or to walk unsupervised or with extended family members or neighbors.
- In general, working women are closer to child and home locations than working men are. This distance is likely to coincide with disproportionate care work responsibilities.
- Increases in distance between parents and children decrease the probability of parents picking up children - the farther parents are away from children, the less likely they will

pick them up; thus, parents who are closer to the children are more likely to pick them up in an emergency. The closer parent is more frequently the mother.

- Car availability significantly affected child pick-up behavior when parents are far away (at least 5 miles) from children, supporting the hypotheses that transport-related care work occurs disproportionately by car and the availability of a car makes parents more likely to plan on retrieving children from school in an emergency.

Many lessons emerge from the interviews and the analysis. First, even though women in this sample do appear to take on far more child-serving transport than their male counterparts, it is not at all clear from the nature or quality of their comments that child-serving mobility is onerous. Instead, both women and men largely conveyed enjoyment around child-serving trips even with normal complaints about bad traffic, terrible Chicago drivers, awful Chicago winters, and unreliable transit service. Our respondents did not really reflect the image constructed around soccer moms in the US who are trapped miserably behind the wheel in suburban sprawl in such popular books as *Suburban Nation* (Duany, Plater-Zyberk, and Speck 2000). While many parents might have preferred to spend their time with their children doing things other than drive around, child-serving trips, disproportionately undertaken by women, were not generally reported as being a chore in the same manner as one would view cleaning out the refrigerator, shopping for groceries, or mowing the yard.

Understanding everyday child-related travel behavior appears to help us understand how families envision their options with regard to evacuation behavior on a household level—with the caveat that most parents do not plan on depending on either their spouse or other trusted caregivers to pick up children. The result: unless cell phones are working and parents can get through to each other, evacuation models should assume that both parents are going to undertake the trip to schools or daycare centers for pick up. That effectively doubles the everyday traffic surrounding schools at peak times, and the consequences on aggregate emergency traffic levels may be significant.

Some public resources, such as buses, may need to be allocated to low-income communities during an evacuation. These resources may not be as necessary for high-income communities since these households are more likely to be able to participate in child-serving activities in an emergency because they are less constrained with time and mobility. Also

pertaining to child-serving activities, school and daycare center staff should incorporate both parents in emergency planning, since the gender difference varies in emergency conditions compared to a normal day, and these institutions should have a way to communicate with parents to inform them of any emergency actions schools or daycare centers are taking. In turn, evacuation and emergency planning should engage both parents in familiarizing them with school practices and with emergency routes to their children's schools.

Schools with good communication with the parents may wish to consider including in their plans alternate pick up sites that are more accessible than their current locations, such as nearby locations just offsite of the school. Alternatively, large schools may benefit from a small number of multiple, coordinated pick-up locations surrounding the school site. These locations should be close to the schools so as not to add to evacuation time.

Finally, the evacuation management strategies should acknowledge the family gathering (both child and spouse) and the preferred meeting at home. Traditional engineering approaches to evacuation management have not addressed this behavior and have focused on moving traffic out of the affected area as efficiently as possible. Some of these strategies include reversing travel lanes and restricting access to particular roads (e.g., ramps); these strategies may hamper family gathering activities and actually worsen conditions by causing drivers to reroute unexpectedly, which could extend evacuation times. If evacuation plans account for the gathering behavior, the timing of the implementation of the strategies becomes important, but more effective.

Chapter 4   Household Gathering Chains in an Evacuation Model: Procedures and Case Applications

The material in this chapter will be submitted for peer review in the near future.

Abstract

Previous studies discovered that household members tend to evacuate as a unit, however, most of the existing transportation engineering based evacuation models treat evacuees as independent and separate entities, and omit the interactions among household members during an evacuation (i.e., parents retrieve children from school, a married person gathers a spouse, or household members return home to unite with other family members). The omission of these behaviors leads to imprecise modeling of evacuation situations. In this study, the authors present a procedure to incorporate household gathering behavior in an emergency into a four-step based evacuation model in order to examine whether and how the network performance will be affected with household gathering behavior taken into consideration. The whole framework was tested in the Chicago metropolitan region for two hypothetical incidents with two different extents of consequence, causing 5-mile and 25-mile radius evacuations. The results showed that household gathering behavior causes deteriorated network traffic performance compared to scenarios omitting this behavior.

Introduction and Background

In the past three decades, a large number of studies have addressed evacuations arising from either natural disasters or manmade incidents. Evacuation traffic modeling efforts have been undertaken since the early 1980's after the nuclear reactor incident at Three Mile Island in 1979. Early models, such as NETVAC (Sheffi, et al., 1982), DYNEV (KLD, 1984) and MASSAC (Hobeika & Jamei, 1985), were established on the aggregate level and based on macro-simulations to cope with nuclear incidents or hurricanes. Later, researchers started to introduce microscopic simulation techniques into evacuation studies. For example, Lämmel, Grethera, and Nagela (2010) model a large scale evacuation on the microscopic level based on a multi agent traffic simulation (MATSim) framework. Pel, Bliemer, and Hoogendoorn (2011), in their review article on dynamic traffic simulation models for evacuations, concluded that in most of these

evacuation models, travel demand is either a model input or estimated in combination with a gravity-model based trip distribution model.

Precisely estimating how many people are involved with an evacuation and when they start evacuating are remaining challenges, but these items play crucial roles in evacuation planning. Previous studies on evacuation demand beginning to address these issues include exploring a variety of factors that influence individual's decisions on whether or not to evacuate (Dash & Gladwin, 2007), estimating the number of evacuees (Fu & Wilmot, 2004, 2006), as well as modeling an evacuation response curve (Fu et al., 2007). Most of these relevant studies operate on the basic assumption that evacuees only conduct a single trip from a single origin to a single destination (which may be appropriate for advanced notice events), and ignore that an evacuation trip could be a chain among household members especially for the case of day-time no-notice evacuations. However, many social scientists found that household members tend to evacuate as a unit (Drabek & Boggs, 1968; Perry, Lindell, & Greene, 1981; Sallee, 2005). Ignoring this behavior will lead to overly optimistic estimations of evacuation time and make certain evacuation strategies (e.g., phased evacuation) or plans infeasible in practice.

Murray-Tuite and Mahmassani started to fill the gap by formulating trip chains and meeting points to represent household interactions. They pre-specified some household information (e.g., household structure, and location of each family member during the daytime), and focused on finding optimal meeting points and optimal trip-chain sequences to minimize the total perceived travel time using linear integer optimization techniques; it is noteworthy that their investigations sought an optimal solution (Murray-Tuite & Mahmassani, 2003). However, ideal situations may not be reached in reality. Modeling real (stated) household gathering behavior is the subject of the present work.

Based on the interviews conducted by Dr. Schweitzer and the Center for Neighborhood Technology (CNT) in the Chicago metropolitan area from July 2008 until January 2009, Liu, Murray-Tuite, & Schweitzer explored these behaviors and developed logistic regression models to predict the probability that a parent picks up a child in two hypothetical emergency cases (see Chapter 3). Liu et al.'s work modeled parents' decision making on retrieving children from school in an emergency based on empirical interview data, and found the relationships between these household behaviors and respondents' demographic, socio-economic, and spatial

characteristics. They found that the probability that a parent picks up a child in an emergency is significantly affected by gender, distance between the parent and the child, and interaction effects of gender and distance: women are more responsible for picking up children in an emergency; increases in distance decrease the probability that mothers pick up a child in an emergency but do not influence fathers' propensities of picking up a child in an emergency. This chapter extends Liu et al.'s work to general household gathering, including gathering a spouse and stopping at home before an evacuation.

Another drawback of the existing evacuation studies is that social scientists' population behavior studies were disjointed with transportation engineers' efforts on evacuation network models (Lindell and Prater, 2007). A large body of studies (e.g., Baker, 1991; Bateman & Edwards, 2002; Dow & Cutter, 1998; Whitehead, et al., 2000) examined how the decision of evacuation varies across the impacted population in terms of endogenous factors (demographic characteristics) and exogenous elements (disaster-related factors). However, only a few of these behavior models were included in transportation evacuation models; most of transportation based models still use subjective participation rates to estimate evacuation demand. Lindell and Prater (2007) reviewed the principle behavioral variable affecting estimates of evacuation time for hurricanes from the perspectives of trip generation and destination/route choice, and pointed out future directions for further integrating mathematical modeling and empirical research, which requires engineers and survey researchers to communicate with each other so that engineers get data to fulfill the models and survey researcher broaden their focus.

This chapter helps bridge the gap between behavior studies and network models. A framework for an evacuation model is presented, which starts from the behavior models that take household gathering into consideration, following the traditional four steps: trip generation, trip distribution, mode choice and traffic assignment. In trip generation, household gathering chains are generated using a discrete choice (Logit) model and the sequence of stops within a chain is determined by following the principle of "nearest first," where the closest household member is gathered before more distant members. In the trip-distribution step, safe super zones (combinations of traffic analysis zones) are determined for each household and mainly reflect the direction of a destination with the least travel time to safety from the last stop within the hot zones. Decision tree based mode choice models were developed to determine evacuation modes.

These first three steps are developed based on the interviews to suit the emergency situations, and traffic assignment is accomplished by built-in algorithms of a traffic simulation package, VISUM. The framework was then tested in the Chicago metropolitan area; by comparing cases with and without household gathering, the affects of household gathering behavior on network clearance were identified.

The major contribution of the study is to utilize empirical interview data on population evacuation behavior to a higher extent by integrating it with widely used transportation network modeling. A practical procedure was developed to generate household evacuation chains, assign temporary destinations, assign modes of transportation, and evaluate network traffic performance with traffic assignment. This framework involves many state of art techniques in the transportation modeling field, such as the module of population synthesizer of TRANSIMS (AECOM, 2010), the decision tree classification for discrete choice modeling, and dynamic traffic assignment to deal with time-dependent demand. The framework can be easily integrated with other advanced techniques and applied in practice to assist evacuation planning and management.

The remainder of this chapter is organized into four sections. The first presents an overview of the data used in this study. The next section depicts the framework of the model and describes each step in detail. Then the framework is applied to hypothetical events in the Chicago metropolitan area and the results are analyzed in terms of total number of trip chains generated and network performance. The final section provides some conclusions and future directions.

Data

Interviews of individuals' responses to hypothetical no-notice incidents pertaining to picking up children and gathering family members were conducted by University of Southern California and the Center for Neighborhood Technology (CNT) in the Chicago metropolitan area from July 2008 until January 2009. The interviews used both random solicitations and snowball sampling to recruit the total 315 participants. Snowball sampling is a method to recruit new participants through acquaintances of existing participants, so that the sample group grows like a rolling snowball (Goodman, 1961). The interviewers pursued snowball sampling through CNT's institutional relationship with community-based organizations throughout the Chicago region.

The interviews included over fifty questions ranging from basic demographic characteristics (i.e., gender, sex, age, household income) to more complicated questions (i.e., commute chain, evacuation trip chain). From the interviews, 59% of parents reported picking up their children from schools/daycare centers during no-notice evacuations; 39% of married interviewees reported gathering a spouse to evacuate together; 32% of respondents would return home to unite with family members and then evacuate when facing a major disaster requiring staying away from home for at least three days. The high proportions of respondents participating in household pick-up and gathering activities in a no-notice emergency, again, indicate the inappropriateness of ignoring family gathering in an evacuation study.

This study explored two hypothetical daytime no-notice incident scenarios: Scenario #1 represents a minor incident causing a small-area evacuation and Scenario #2 represents a major incident requiring a large-area evacuation. In Scenario #1, an incident causing workplace and school evacuation without home evacuation (i.e., home is safe), respondents have been informed that they must evacuate their worksite immediately and stay away for the rest of the day, they have 5 minutes to leave their worksite, and their child's school must be evacuated if it is within 5 miles of the worksite. In Scenario #2, an incident causing workplace and school evacuation with home evacuation, respondents have been informed that they must evacuate their worksite immediately and that their home area has also been subject to an evacuation, they have 5 minutes to leave their worksite, their child's school will be evacuated, most of the surrounding region will be evacuated as soon as possible, and they will have to be away from their home for at least three days.

Model Framework

When an incident occurs, for anyone affected who is either in the dangerous area or has family members inside, there is a series of decisions to make, e.g., will he/she evacuate, when he/she will depart, where he/she will evacuate to, and by what mode he/she will leave. Beyond these issues, there are other concerns for family household members, e.g., will he/she (if a parent) need to pick up children from school, will he/she (if married) gather a spouse to evacuate together, or if multiple stops are involved, in which sequence should he/she arrange a gathering chain? To deal with this series of decisions, a model procedure was developed in the framework of the traditional four-step model, as illustrated in Figure 4.1.

The procedure starts from estimating synthetic households based on Census data. Next, household members are located within the network during the daytime by determining their work and school locations. Then vehicles owned by a household are allocated to individuals so that each individual is characterized by whether he/she has access to private transportation. After specifying individual characteristics (e.g., gender, access to private transportation, socio-economic characteristics, etc), we adopted discrete choice models (developed in Chapter 3) to predict each individual's gathering actions. For those who have to stop at more than one place during an evacuation, we sequence those stops on a basis of "nearest-first." Sequencing evacuation chains is followed by determining loading departure time for evacuees, assigning destinations, and estimating modes they would use to evacuate. Finally, a dynamic traffic assignment method is adopted to assign time-dependent evacuation chains to the network to evaluate network evacuation performance. The details of these steps are presented below.
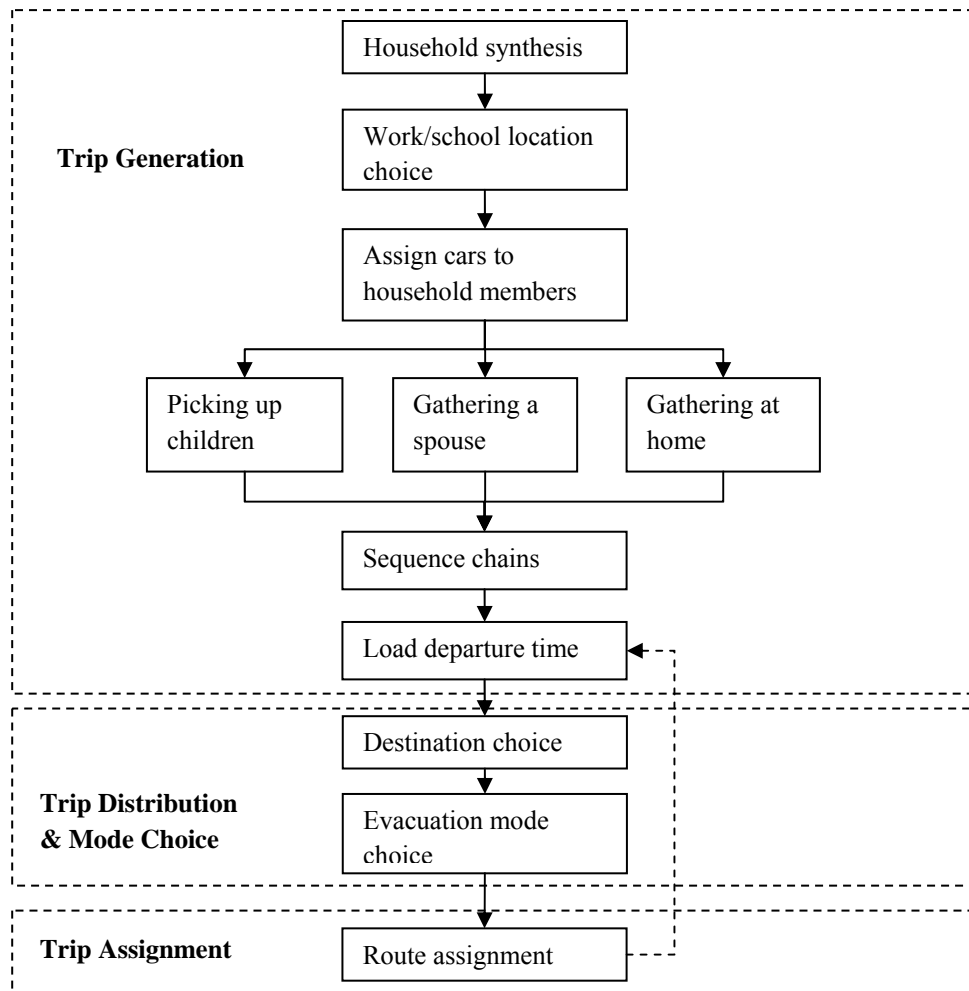
Figure 4.1. Framework of the Evacuation Model Considering Household Gathering

Population Synthesis

TRANSIMS Population Synthesizer

The presented household-gathering model was developed on a disaggregate level, and the disaggregate level of data about the entire relevant population can be estimated (so called synthetic population) in many ways. In this work, we use the Population Synthesizer module in TRANSIMS, which, using Census Standard Tape File 3A (STF-3A) and the Public Use Microdata Sample (PUMS), estimates the proportions of households at the census tract or block group level that fits in each demographic household category by applying the method of iterative proportional fitting (IPF) (Beckman et al., 1996). The module can extract attributes contained in the Census data, including household income, vehicle ownership, age of household members,

gender, education, and so on. The module can also locate each household to the network according to land-use characteristics.

The TRANSIMS Population Synthesizer requires users to identify a set of attributes for cross classification to replicate a household from the PUMS data for a given zone. The set of attributes are controlling variables for IPF to estimate proportion of households. In this study, three attributes are selected to be cross-classification attributes: household income, age of the householder, and household size, which are broken into 16, 8 and 7 categories, respectively. The population synthesizer generates all other attributes based on the Census data falling into these categories.

Work/School Location Choice
The next step is to locate synthetic populations on the road network, that is, to identify household members' daytime locations (i.e., work/school locations). In a activity-based model for planning purposes (such as TRANSIMS), work/school location choice is part of destination choice and is generally modeled as a discrete choice model (e.g. logit) with the utility of a transportation analysis zone (TAZ) as a function of land use characteristics and travel cost between home and work/school (Bernardin et al., 2009; Jonnalagadda et al., 2001).

However, detailed land-use information may not be available in some cases, such as ours. This study modeled work/school location in a more empirical and simple way based on travel distance distributions obtained from the interviews, home-based work (HBW) trip attractions of each TAZ from the planning model provided by CMAP, and the number of schools in each TAZ. The method involves two steps: first, find a distance range that follows the surveyed distribution by using random numbers between 0 and 1 and extract all zones that fall within this distance range; second, calculate the probabilities of a TAZ being selected as a work/school location for those extracted zones in the first step (the probabilities are weighted by HBW trip attractions for work location choice and by number of schools for school location choice). Calculate cumulative probabilities so that each TAZ corresponds to a particular interval, then generate another random number and select the TAZ corresponding to the interval in which the random number falls. As TRANSIMS also provides place of work PUMS for employed populations, the extracted zones need to be within the place of work PUMS for work location choice. Attempting to reflect reality as much as possible, two additional rules were generated for school location choice: 1) if two

children in one household are in the same grade, there is a 90% possibility that they are attending the same school (the number was observed from the interviews); 2) if a child is 10 miles away from home, there is a 70% chance that he/she is less than 2 miles from parents' work places. Work location choices are determined first, and then school locations, so that school locations are conditioned on both home locations and parents' place of work in some cases, which can remedy the independence of two spatial choices to a certain extent.

The conventional gravity-based activity location choice model finds a TAZ in one step; however, it requires detailed land use information and calibration of parameters as well. The method introduced here treats travel distance as the primary basis for work/school choice. Controlling for travel distance is believed to be acceptable for this study. In the future, other conventional discrete choice models based on more extensive information can be investigated for work/school location choice.

Assign Car Availability to Synthetic Populations
This step determines whether a synthetic person has a car available to use. A rule-based approach is adopted due to the lack of detailed information on car usage; similar methods were used by researchers for modeling activity-based travel demand (Hatzopoulou et al., 2007). The primary rule is that if one commutes to work by car, a car has to be assigned to him/her. Cars owned by a household are assigned to household members in the order of: (1) workers who commute by car, (2) other adults, and (3) children over 16 years old. No more one car is assigned to one person. All cars are assigned in a household following the principle of first-in, first-serve. TRANSIMS population synthesizer lists household members in the order of householder, husband/wife, children and others. As a result, the approach can also ensure that householders are assigned with a car with priority.

Generating Household Gathering Chains

This step is to generate evacuation demand considering household gathering. According to Liu et al.'s unpublished work in Chapter 3, evacuation behavior related to household gathering can be modeled by a binary logit model as shown in Equation (1). *P* represents the probability of gathering others; *U* is the utility function of gathering. The estimated logit models were applied to synthetic households, so that each member of synthetic households was associated with a decision on whether to gather others or not.

$$P = \frac{e^U}{1+e^U} \tag{1}$$

Household gathering refers to gathering a child, a spouse, parents, in-laws, and other non-family members. Based on the interviews conducted in Chicago, only gathering a child and a spouse can be modeled with satisfactory explanatory power due to the sample size. We could not find a satisfactory model to estimate the probabilities of the other types of gathering which the dataset revealed (5% reported gathering adult children, 12% reported gathering parents, and 20% reported gathering non-family members). The models and parameter estimates reflect the interviews, and may not represent the general situations due to the limitation of the interview sample size.

Gathering a Child

The logit model predicting the probability that parents pick up children was established for employed (or volunteer) parents with their child staying outside the home during the daytime. Equations (2) and (3) are for Scenario #1 and Scenario #2, respectively. Equations (2) and (3) were obtained after testing all possible combinations of potential influencing factors in the software R because of their goodness of fit. For an individual not a parent of children under 18, no child pick up behavior was needed; and for stay-at-home caregivers, a fixed proportion picked up children (90% is used in the subsequent numerical study based on the interviews).

$$U_C^{S1} = -1.2899 - 1.3407 \times male + 1.0624 \times cauc + 2.0220 \times CDIA \tag{2}$$

$$U_C^{S2} = 1.1669 - 2.9859 \times male - 0.1572 \times dist + 1.0951 \times car + 0.1499 \times male \times dist \tag{3}$$

where,

male: a binary variable, 1 if a parent is male, 0 if female;

cauc: a binary variable, 1 if a parent is Caucasian, 0 if non-Caucasian;

CDIA: a binary variable, 1 if having a child within 5 miles of the worksite, 0 otherwise;

dist: travel distance from a respondent's workplace to a child's location (miles);

car: a binary variable, 1 if having a personal car to use, 0 otherwise;

The logit model assumes that unobserved factors follow a Gumbel distribution, and this distribution implies the independence of irrelevant alternatives (IIA) assumption for the

multinomial logit model (i.e. unobserved factors are uncorrelated over alternatives) (Train, 2003). The IIA assumption is easy to justify for the cases that only one child is involved, as the alternatives (pick up the child or not) are distinct. However, provided that the models are estimated based on the dataset with parents' decisions towards all children included, meaning that repeated observations of the same parent may appear, a correlation among observations for the same respondent may exist, and the IIA assumption may no longer hold. Therefore, for the respondents having more than one child who needs to be picked up, one arbitrarily selected child (called Child 1, the child who the respondent thought of or listed first during the interviews) was included to build the models (Equations (2) and (3)); consequently, two questions arose: 1) can the models based on Child 1 can also represent parents' decisions towards another child (i.e., Child 2, who is in a different location from Child 1), and 2) does a combined model which estimates parents' behavior towards Child 1 and Child 2 simultaneously exist to explain the behavior better than a single model that estimates parents' behavior towards Child 1 and Child 2 separately.

The first issue concerns the ability of the models estimated in context i to describe observed individual choices in a new context j, which is referred to as transferability of model parameters. Atherton & Ben-Akiva (1976) defined transferability test statistics (TTS) as $-2(l_j^*(\theta_i) - l_j^*(\theta_j))$, where $l_j^*(\theta_i)$ is defined as the log of the likelihood that the observed data in context j were generated by the model estimated in context i; $l_j^*(\theta_j)$ is defined as the log-likelihood of the model originally estimated in context j (Ortúzar & Willumsen, 2001). TTS is chi-square distributed with degrees of freedom equal to the number of model parameters; it tests the null hypothesis that the parameter estimates in context j are equal to the ones in context i. The test is asymmetric and the proven transferability from context j to i does not guarantee the accepted transferability from context i to j (Ortúzar & Willumsen, 2001). The null hypothesis is rejected if the calculated p-value is lower than the desired significance level α (Bekhor & Prato, 2009).

In the context of this study, for Scenario #2, we examine the null hypothesis that model parameters for Child 1 are equal to those for Child 2 using the TTS. The log of the likelihood that the data for Child 2 are generated by the model estimated based on Child 1 is -56.58, the log-likelihood of the model estimated based on Child 2 is -54.69, so the transferability of model

parameters is verified from Child 1 to Child 2 cannot be rejected because of $p = 0.286$ (*TTS* = 3.78, df =3). Analogously, the log of the likelihood that the data for Child 1 are generated by the model estimated based on Child 2 is -90.52, the log-likelihood of the model estimated based on Child 2 is -86.68, so the transferability of model parameters is marginally accepted from Child 2 to Child 1 at the significance level of 5% because of $p = 0.053$ (TTS = 7.68, df =3). As a result, we concluded that models estimated for Child 1 can be used to represent the parent behavior towards every child in a household.

We introduce marginal homogeneity to further investigate the relations between a parent's choice towards Child 1 and Child 2, which can be seen as repeated measures in the same subject under two different conditions. Marginal homogeneity refers to equality or lack of significant difference between two or more conditions for each subject for the same conceptual measurement (Agresti, 1997; White et al., 1982). A non-parametric method, McNemar's test (McNemar, 1947), was established to examine marginal homogeneity for binary outcomes, and used in this study. McNemar's test statistic of 0.111 ($p = 0.74$) provides insufficient evidence for rejecting the null hypothesis that no significant difference exists when the same parent makes the decisions on picking up children in two different locations in an emergency, i.e., $\beta_{C1} - \beta_{C2} = 0$, where β_{C1} and β_{C2} are parameters reflecting condition effects of pick up behavior for Child 1 and Child 2, implying one model can be used for both conditions (Child 1 and Child 2). In other words, no child difference (or preference) was found in a parent's child pick-up behavior across children, which is in line with common sense that parents would treat each child equally in the case of an emergency.

We then compare four models in terms of goodness of fit for both Child 1 and Child 2: Model I – use the model estimated based on Child 1 for both Child 1 and Child 2; Model II – use the model estimated based on Child 2 for both Child 1 and Child 2; Model III – use the model estimated based on Child 1 for Child 1, and use the model estimated based on Child 2 for Child 2; Model IV – use the model estimated based on Child 1 for Child 1, and use the model considering the outcome towards Child 1 for Child 2. Table 4.1 displays parameter estimates of the four models and associated log-likelihood for the combination of Child 1 and Child 2. From Table 4.1, Model III can be seen as a full model; comparing Model I (a restricted model) with Model III, the log-likelihood ratio statistics is -2(-39.3657-(-35.8629)) = 7 (df=3, $p = 0.072$), so the null

hypothesis that the model parameters associated with Child 2 are 0 cannot be rejected. Table 4.1 also shows that the log-likelihood for Model IV is -45.5138, indicating the log-likelihood fitting both Child 1 and Child 2 even decreased when choices for Child 2 were estimated with outcomes for Child 1 taken into consideration. To summarize, on the basis of the statistical analysis above, the models estimated using the Child 1- related data are used to predict a parent's behavior of picking up a child in an emergency.

Table 4.1. Estimates and Log-Likelihoods of Four Models for Scenario #2

	Model I	Model II	Model III		Model IV	
	Child1	Child2	Child 1	Child2	Child 1	Child2
male	-2.9859	-4.2885	-2.9859	-4.2885	-2.9859	-3.9329
dist	-0.1572	-0.1600	-0.1572	-0.1600	-0.1572	
male × dist	0.1499		0.1499		0.1499	
car	1.0951	3.1751	1.0951	3.1751	1.0951	
PickupChild1						3.5964
		Dataset - Child1 and Child2 (43 observations)				
Log-likelihood at estimates	-39.3657	-40.1929	-35.8629		-45.5138	

Applications of the child pick-up models to the synthetic population follow the logic outlined below. The logic ensures that all children who are not staying with either parent at the moment of disaster occurrence are picked up; the logic also allows double pick-ups (by both parents), which was found from the interviews, especially if parents could not communicate by cell phone. The child pick-up model was established for employed (or volunteers) parents, and a fixed probability of 0.9 for stay-at-home caregivers was applied (the value was estimated from the interviews).

> *for a household i,*
> > *for a child j,*
> > > *if child j is not staying with either parent;*
> > > > *for the householder in household i;*
> > > > > *apply child pick-up model towards j;*
> > > > *for the spouse in household i;*
> > > > > *if the householder does not decide to pick up child j,*
> > > > > > *then the spouse will pick up child j;*
> > > > *else,*
> > > > > *apply child pick-up model towards j;*

The above logic does not consider communications between parents; when accounting for communication, a spouse's behavior can be determined accordingly without applying child

pick-up models, as listed below. In the below logic, we consider the householder first and then the spouse, except when a spouse is a stay-at-home caregiver, then we consider the spouse first, and the householder second.

> *if the householder does not decide to pick up child j,*
> > *then the spouse will pick up child j;*
> *else,*
> > *the spouse will not pick up child j;*

Gathering a Spouse

Spouse-gathering behavior was analyzed based on the sub-dataset of married respondents from the interviews (216 observations). Spouse gathering, as well as home gathering discussed below, is for Scenario #2. Scenario #1, as a minor incident, requires no home evacuation, thus, not much spouse gathering or gathering at home was observed in the interviews. Gender, age and ethnicity were not significantly associated with spouse-gathering. Men and women are almost equally likely to gather their spouses in an emergency. U_s is the utility function of gathering a spouse, estimated using R, as shown in Equation (4).

$$U_s = -2.3594 + 3.3884 \times car + 2.6730 \times scoll - 1.6473 \times coll - 0.0851 \times dist \times scm$$

(4)

where,

   scoll: a binary indicator of spouse education level, 1 if a spouse has a college degree, 0 otherwise;

   coll: a binary indicator of evacuee education level, 1 if an evacuee has a college degree, 0 otherwise;

   distc: travel distance from the respondent's workplace to spouse's workplace (miles);

   scm: an indicator of spouse commute mode, 1 if a spouse commutes by car, 0 otherwise.

Gathering at Home

The interviews revealed that 32% of respondents reported returning home and then evacuating together with their family members for a large-scale evacuation (Scenario #2). As gathering family members other than spouses cannot be modeled due to the small sample of the interviews, simulating the behavior of evacuees gathering at home, to some extent, can reflect the actions of

gathering other family members. U_{hg} is the utility function of gathering at home, estimated using R, as shown in Equation (5).

$$U_{hg} = -2.0217 - 0.5748 \times female + 1.3703 \times parent + 1.0141 \times minors + 0.2983 \times adults - 1.0924 \times parent \times minors \tag{5}$$

where,

female: a binary variable, 1 if an evacuee is female, 0 if male;

parent: a binary variable, 1 if an evacuee is a parent of a child under the age of 18, 0 otherwise;

minors: number of children under the age of 18 in the household, 0 otherwise;

adults: number of adults in the household, 0 otherwise.

Sequencing Stops

The interviews did not reveal any strong evidence for a model by which to sequence the pick-up and gathering chains. Take Scenario #2 as an example, among 315 interviews, 30 respondents stop more than one place to pick up children, of which 10 respondents pick up the child closest to their origins first, and 12 respondents pick up the youngest child first. Therefore, no strong evidence indicated that either location or age of children affects the sequence of child pick-up chains. The fact that children are close to each other could explain a lack of effect of children's locations on parents' pick-up sequence. In this model, it is assumed that evacuees sequence their chains of picking up children and gathering others in terms of distance, e.g., they will pick up the children closest to them first.

Departure Time

Many distributions were used to model the time when evacuees start evacuation, including instantaneous departure, a uniform distribution, a Rayleigh distribution, a Poisson distribution, a Weibull distribution, or a sigmoid curve, according to a review by Pel et al. (2011). A sigmoid curve, formulated by Radwan et al. (1985) as Equation (6), was used to estimate departure time in many evacuation models such as TEDSS (Hobeika, 2002; Hobeika, et al., 1994) and MASSVAC (Hobeika & Jamei, 1985).

$$P(i) = \frac{1}{1+e^{-\alpha(i-T)}}$$

(6)

where,

  P(i):   cumulative percentage of total number of evacuees generated at time *i*;

α: a parameter reflecting evacuees' response rates;

T: half loading time, at which half of the total evacuees are loaded on the network.

In this study, a sigmoid curve is used to load evacuees on the network. *T* is predefined to be 2 hours, and α is predefined to be 2.5. Figure 4.2 shows the sigmoid curves with different response rates, α, for the half loading time of 2 hours. As illustrated in Figure 4.2, a high value of α produces more concentrated departure time.
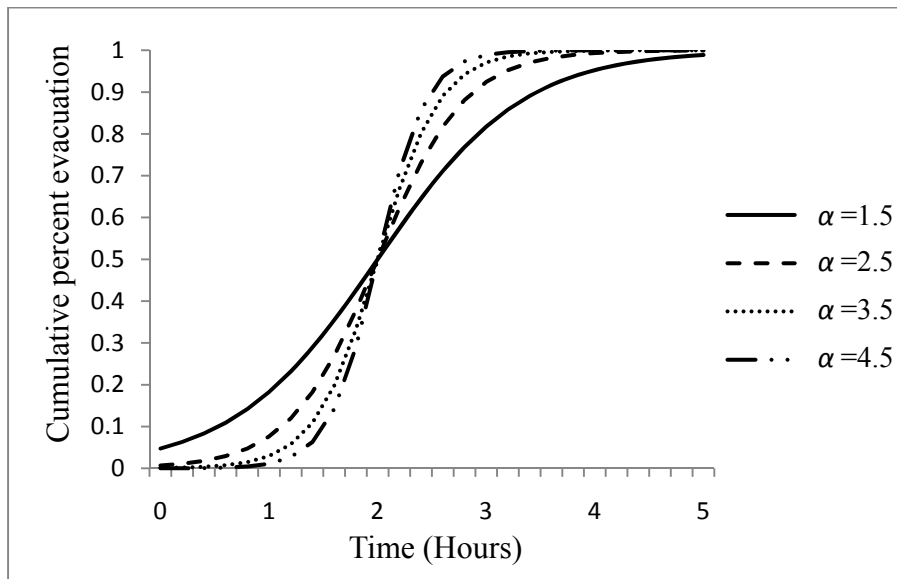
Figure 4.2. Sigmoid Curves with Half Loading Time of 2 Hours

Mode Choice

Traditionally, travel mode choice, as a discrete choice, is modeled by multinomial logit (MNL) or nested logit (NL) models (Ben-Akiva & Lerman, 1985); recently, emerging data-mining techniques have been applied to model commute mode choice, such as neural networks (Hensher & Ton, 2000; Xie, Lu, & Parkany, 2003; Zhang & Xie, 2008), decision trees (Wets et al., 2000;

Xie et al., 2003) and support vector machines (Zhang & Xie, 2008). Discrete choice models (i.e., MNL, NL) use the utility maximization rule to determine choice; however, in a daytime no-notice evacuation, it is understandable that mode choice also depends on commute modes, which is hard to incorporate into utility functions. Furthermore, as the interview was not designed for the purpose of normal day mode choice analysis, some data that are important to formulating an individual's utility of choosing a transport mode, such as in-vehicle and out-of vehicle travel time and transit fare, were not included in the interviews. Decision tree (DT) is a classification method which constructs a tree with a set of rules. DT, as a rule-based classifier, is a "white box", which is transparent to users and easy to interpret. DTs have been recently applied to discrete choice behavior analysis, and achieved considerable benefits for prediction performance (Thill & Wheeler, 2000; Wets, et al., 2000; Yamamoto et al., 2002). Therefore, in this study, DT is adopted to model mode choice for evacuation situations.

The input variables of the DT models include individuals' gender, age, possession of a driver's license, access to a personal car, commute mode, number of adults in the household, number of cars in the household, and child pick up decision. The output variables are mode choice in evacuations, notated as: 1 - driving alone, 2 - taking public transit or taxi, and 3 – carpools; no commute and walking or riding a bicycle are omitted due to the fact that they are hardly used in an evacuation case, revealed in the interviews. Different tree structures were developed using the programming language R for the two scenarios - Scenario #1 and Scenario #2, as shown in Figure 4.3. Basically, for Scenario #1, commute mode is the dominating factor to determining evacuation mode; for Scenario #2, whether an individual has access to a private car during an evacuation is the most important factor to determining evacuation mode, and it is noteworthy that parents' behavior of picking up a child is the second determinant. In Scenario #2, a large-area evacuation which is also a home evacuation, commute modes may not significantly affect travel modes for evacuation, while in Scenario #1, a small-area evacuation without home clearance, commute modes become significant factors.

The classification techniques like decision trees are unstable: small variations in the training set lead to different model topologies and different predictions for the same testing samples (Last et al., 2002). This instability problem certainly raises a question about which model should be used for prediction. To deal with this problem, the whole dataset was divided

into two sets by proportion: a training data set (80%) and a testing set (20%); a DT was built using the training set and tested on the testing set. A correct rate (CR) of the testing set, the portion of correctly classified samples, is used to evaluate the performance of a classification tree. Due to random partitioning of the data set, each time running a single decision tree gives different tree structures and different accuracy rates. The DT method was performed multiple times (more than 50 times in this study). After evaluating each tree in terms of CR, frequency of appearance and rationality of tree structures, a classification tree which is believed to a reliable and meaningful tree was selected for each scenario, as shown in Figure 4.3. The CRs of the selected trees are 80% and 85% for Scenario #1 and #2, respectively, which is acceptable from the prediction perspective.

Figure 4.3 shows the apparent difference of mode choice patterns for the two incident scenarios. In a minor incident (Scenario #1), what mode evacuees would choose to evacuate highly relies on their normal commute mode; while in a major incident (Scenario #2), car availability appears to be a dominating factor to determining evacuation modes.

Notations used in Figure 4.3 are,

NoCars: number of cars in a household;
CommuteMode: transportation modes an individual use to commute (0 - no commute, 1 - driving alone, 2 - taking public transit or taxi, 3 - walking or riding a bicycle, and 4 – carpools);
PickupChild: 1 if an evacuee decisions to pick up a child, 0 otherwise;
CommuteDistance: travel distance from home to work (miles);
Car: 1 if an individual has access to a private car, 0 otherwise.
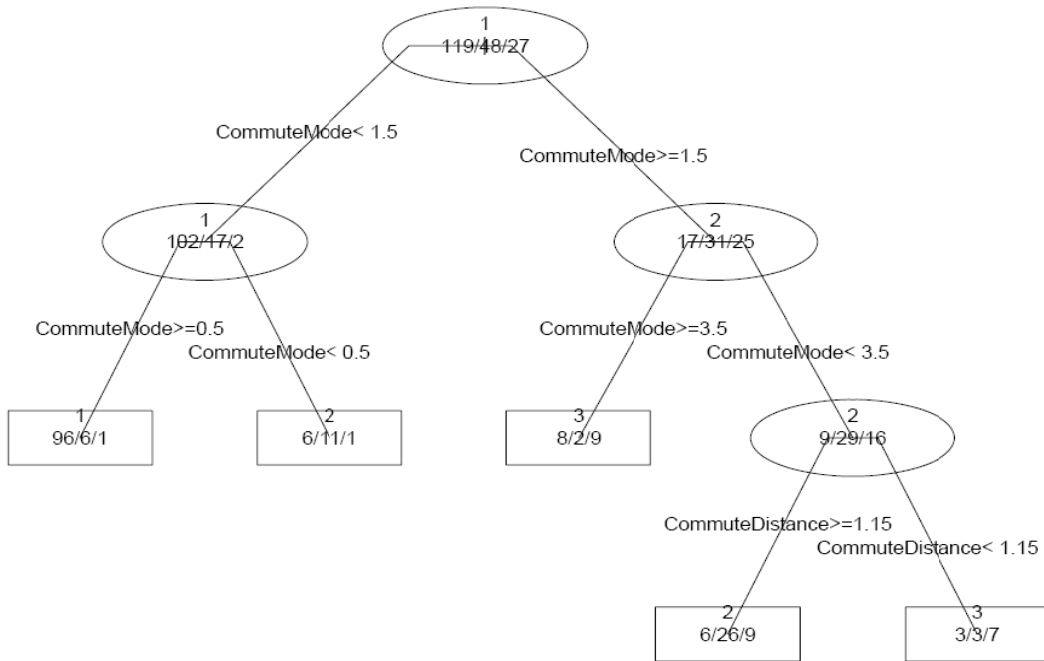
a) Scenario #1
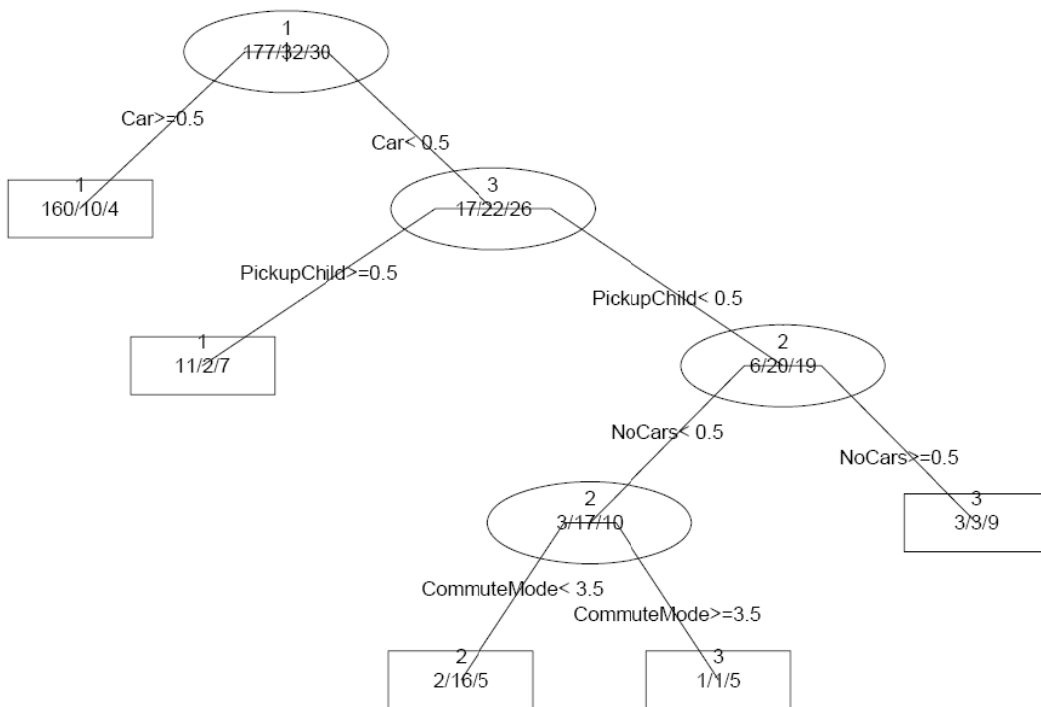
b) Scenario #2
Figure 4.3. Classification Tree for Evacuation Mode Choice

*The numbers inside a node refer to the number of observations of each mode in that node. For example, 160/10/4 represents in that terminal node, there are 160 observations of driving alone, 10 observations of taking public transit or taxi, and 4 observations of carpools.

Destination Choice

Under a no-notice evacuation, it is feasible to assume that evacuees do not choose a route to their actual destination when they are still in a dangerous zone; instead, they choose a route to leave a dangerous zone with minimum travel time. Once they reach a safe zone, they will continue their trip to their final destination (Pel, et al., 2011). Based on this assumption, in this study, destination choice is modeled in a practical way, following the steps: 1) determining several safe super zones by directions (each safe super zone covers multiple TAZs in a direction), 2) find the closest safe super zone for an evacuee with minimum evacuation time from his/her origin (or last stop within the dangerous zone if he/she gathers anyone) to this safe super zone, 3) randomly assign a TAZ within the safe super zone to the evacuee. Since what happens outside a dangerous zone is not the concern of this evacuation study, it is also acceptable to assign a closest TAZ, termed as a *proximate destination* by Lindell and Prater (2007), outside the dangerous zone to an evacuee directly. The reason that introducing a safe super zone rather than a *proximate destination* is because assigning tremendously heavy demand to a TAZ will cause an unrealistic blocking problem for dynamic traffic assignment.

Sample Application: Simulation and Evaluation

Incidents, Assumptions and Testing Cases

The presented model framework was tested in the Chicago metropolitan area. The Chicago Metropolitan Agency of Planning (CMAP) provided the transportation planning model built in EMME2, which was then converted to PTV VISUM by the authors, as shown in Figure 4.4 (the thicker, blue lines indicate freeways; the thin, gray lines indicate arterial roads; the orange shading marks the City of Chicago). CMAP provided the road network and demand estimates for eight time periods, as this study investigated incidents occurring during school hours, the time period from 10:00 am to 2:00 pm was chosen as a base model. The CMAP model also includes rail and bus line information as well as transit demand estimations, which allows the authors to apply the presented framework on a multi-modal transportation system.
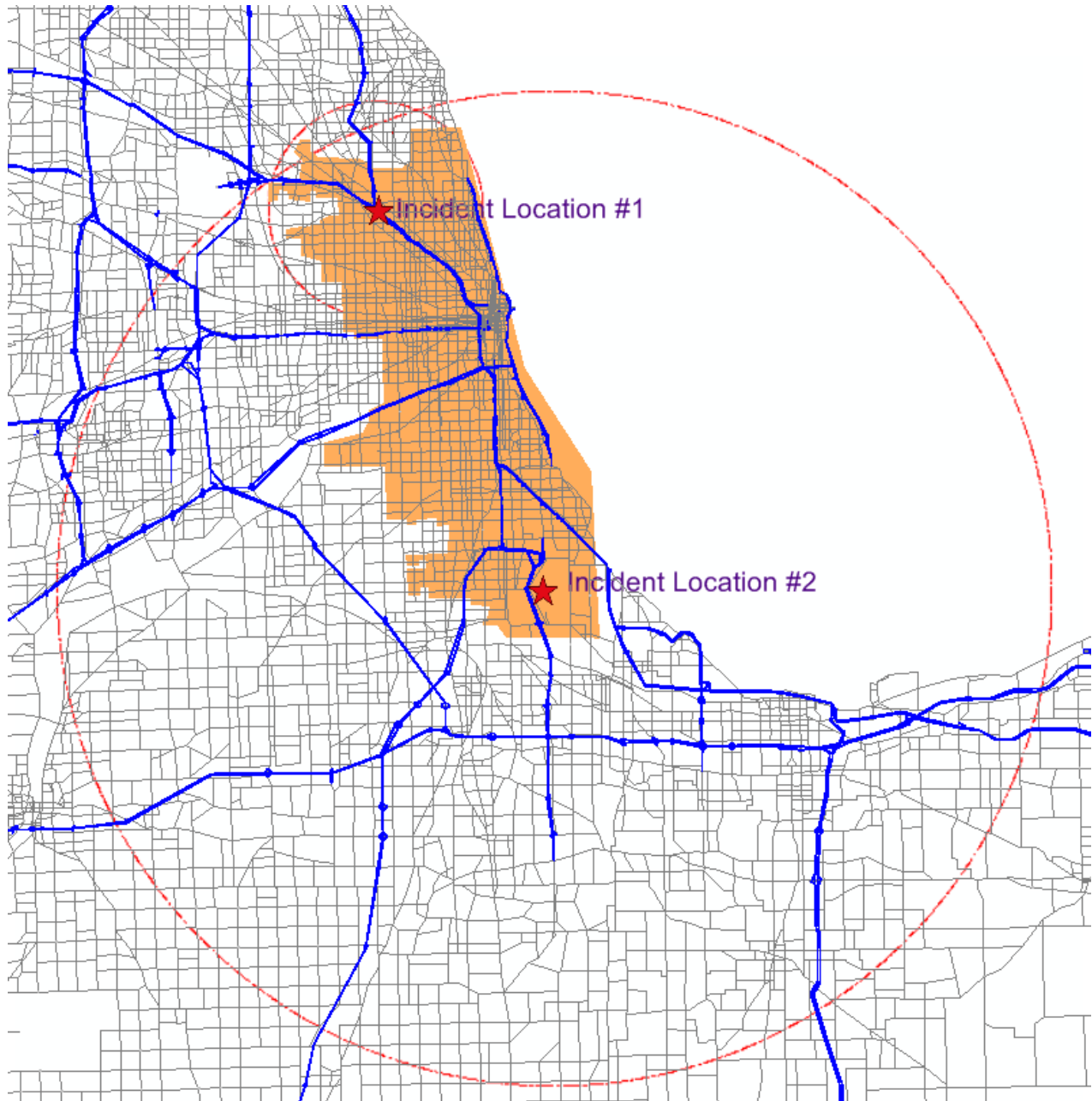
Figure 4.4. Road Network of the Study Area in VISUM

Two hypothetical no-notice incidents were examined: 1) a minor incident occurs at a major road interchange (Location #1, marked as a red star in Figure 4.4), leading to an evacuation of a 5-mile radius; 2) a major incident occurs at the location of a company running a hazardous waste treatment (see Figure 4.4), requiring an evacuation of 25-mile radius. The severity and consequence of the two incidents corresponds to the descriptions of Scenario #1 and #2 from the interviews, respectively, and thus are indicated as Scenario #1 and #2 in this sample application. The investigation here is for a general emergency case rather than an actual or

specific disaster. Incidents are assumed to occur during the school time in order to consider child pick-up behavior.

The sample applications adopts the following assumptions regarding incidents,

- disasters occur during school hours (from 10:00 am to 2:00pm);
- disasters are evacuation-required types, not the kind of circumstance in which schools are locked down;
- no shadow evacuees are considered, the evacuation radius is mandatory, and only people who are in the dangerous area or have family members inside are considered as evacuees; and
- no shelter-in-place strategies are considered, representing worst case demand levels. .

The sample application also makes the following assumptions regarding household gathering behavior in an evacuation:

- sequencing household pick-up and gathering activities in an evacuation is predominantly determined by locations of these activities; in particular one will always gather the household member closest to him/her;
- concerning spouse gathering, once a person decides to gather his/her spouse in an emergency, the next decision to make is where to gather her/him. While the interviews do not include complete information on spouse gathering points, generally, both home and a spouse's workplace are major gather points. In this study, for simplification, we estimated spouse gathering locations based on the results of home gather decisions, following the predefined rules - if one with a need of gathering the spouse also decides to return home to gather family members during an evacuation, he/she is assumed to gather the spouse at home; if he/she will not gather family members at home, he/she is then assumed to gather the spouse at the spouse's workplace; and
- the reuniting of spouses with other family members occurs at home. This reuniting at the home was statistically analyzed for the large scale evacuation scenario (Scenario #2); while gathering them somewhere else was not able to be modeled using statistical methods in this study, because of the small size of the valid sub-dataset (e.g. only 16

respondents reported gathering adult-age children). Gathering family members (except a spouse) somewhere other than home is not taken into consideration here.

This study focuses on examining evacuation behavior related issues, therefore, only behavior related issues are included in the basic testing cases. Two basic cases are tested in this case application for the two incident scenarios, which are,

1. **Baseline Case -** without considering any household pick-up and gather behavior, that is, everyone evacuates themselves in the most efficient way. In this case, it is assumed that schools have ability to move students to safety and parents recognize this ability;

2. **Gathering Case** – considering household pick-up and gathering. In this case, it is assumed that schools do not have ability to move students to safety, or schools have this ability but parents are not aware of it. Spouse gathering and home gathering are only applied for Scenario #2, because in the interviews, home gathering is not valid for scenario #1 and spouse gathering is only recorded for Scenario #2. Since it is assumed that cell phones are not operational, parents do not know each other's actions regarding picking up children. The case allows for considering child double pick-ups by both parents, which was found quite often in the interviews.

Neither certain evacuation management strategies (e.g., contra flow, phased evacuation, etc.) nor evacuees' departure time was the major focus of this study, however, these issues may significantly affect the evacuation efficiency, so for a large-area evacuation scenario (Scenario #2), different departure times were applied for evacuees as sensitivity analysis.

Evacuation Chain Estimates

As shown in Figure 4.4, the evacuation area for Scenario #2 covers most of the evacuation area for Scenario #1. In Scenario #2, the evacuation area includes both Illinois and Indiana. TRANSIMS generates synthetic populations for the areas involved in an evacuation; the summary of synthetic populations for both states is shown in Table 4.2. From Table 4.2, for the Illinois part, of all synthetic households, 66.7% are families, 48% are married-couple families, and 33.1% have children under 18 years old; these values from Census 2000 data for the City of Chicago are 59.6%, 35.1% and 34.3%, for Illinois are 67.6%, 51.3% and 36.2% (Census, 2000). Average size of synthetic household is 2.7; while according to Census 2000 data for City of

Chicago the values are 2.67, and for Illinois the values are 2.63 (Census, 2000); thus, average household size is slightly larger, but rounding to the same number of decimal places is roughly the same. By comparing with the Census data, synthetic households generated by TRANSIMS are reasonable in terms of household structure. Comparing synthetic households and Census data for the Indiana portion, the same conclusions can be reached.

Table 4.2. Summary of Synthetic Households Generated by TRAMSIMS

	Illinois		Indiana	
	Number	Percent	Number	Percent
Households	2,244,980		232,924	
Family households	1,498,162	66.7%	164,983	70.8%
Married-couple family	1,078,169	48.0%	121,508	52.2%
With own children under 18 years	743,511	33.1%	78,942	33.9%
Persons	6,066,384	2.7^a	614,333	2.6^a
Vehicles	3,264,946	1.5^a	398,762	1.7^a

[a] Average value per household.

      Table 4.3 summarizes the number of households (populations) involved in the two hypothetical incidents (generated by the trip generation step in the presented framework). In Scenario #1, 523,817 households have members inside the impacted area when an incident occurs and are considered as households directly involved in the evacuation, of which 27% have their own children under 18 years old inside the dangerous area, i.e., 27% have a need of picking up a child, and 41% have either one of the spouses in the dangerous area and have the potential to conduct spouse gathering; in total, 648,675 people will evacuate, of which 58% have a private car to use. In Scenario #2, for the Illinois part, structures of households involved in the evacuation show similar patterns with Scenario #1, with higher proportions of married-couple households and households with their own children under 18 years, which is consistent with the fact that most of the impacted areas for Scenario #1 is in the City of Chicago (shown in Figure 4.4) and the City of Chicago has a lower proportion of family households than the surrounding area of Illinois. For Scenario #2, the Indiana part only contributes 11% of the total evacuees, while, both family household compositions and car availability to evacuees are higher than Illinois.

Table 4.3. Summary of Involvement of Synthetic Population in an Evacuation

| | Scenario #1 | | Scenario #2 | | | |
| | | | Illinois | | Indiana | |
	Number	Percent	Number	Percent	Number	Percent
Households involved with an evacuation	523,817		1,780,816		211,030	
Family household involved with an evacuation	280,807	54%	1,153,249	65%	146,025	69%
Households with needs to pick up a child	138,859	27%	504,778	28%	65,966	31%
Evacuating married-couple households	216,110	41%	819,978	46%	108,245	51%
Evacuees (adults involved with an evacuation) [a]	648,675		3,035,346		371,069	
Evacuees having access to private cars	378,965	58%	2,067,026	68%	305,104	82%

[a] only adults (18 years old and over) are counted.

Tables 4.4 and 4.5 show the numbers of persons and trips involved in an evacuation for Scenario #1 and Scenario #2. In Scenario #1, the estimates of the total number of persons involved with an evacuation are 648,675 for the baseline case. When considering child pick-up behavior, the estimates are 773,417 persons, an increase of 19% compared with the baseline case and the associated trips increase by 60%; the child pick-up model was applied to those parents who are in the dangerous zone or their children are. So the total involved households are 189,071 (greater than the relevant number in Table 4.3- 138,859), which reflects the findings revealed by the interviews that parents who need to evacuate themselves consider picking up their children during the trip even though the children are not in the hot zone. Estimates of double pick-ups (both parents go to the same place to pick up a child) are 37,152 households (20% of households), and on average, 1.32 parents are involved with picking up children. In scenario #2, 3,406,415 persons either work or stay home inside the hot zone when a hypothetical disaster occurs; when children are in need of being picked up, 793,743 adults are estimated to pick up children from school. The double pick-ups are 64,999; on average, 1.21 parents participate in gathering children from school.

Table 4.4. Number of Synthetic Persons, Households and Trips for Incident Scenario #1

			# of Persons		# of Trips	
			Number	Percent	Number	Percent
Baseline	Drive alone		341,981	52.7%	341,981	52.7%
	By transit		273,780	42.2%	273,780	42.2%
	Carpool		32,914	5.1%	32,914	5.1%
	Total		648,675		648,675	
Child pick-up	Drive alone	Child pickup	168,610	21.8%	343,520	33.1%
		Non-pickup	267,726	34.6%	267,726	25.8%
	By transit	Child pickup	71,979	9.3%	152,708	14.7%
		Non-pickup	227,814	29.5%	227,814	22.0%
	Carpool	Child pickup	8,143	1.1%	16,898	1.6%
		Non-pickup	29,145	3.8%	29,145	2.8%
	Total		773,417		1,037,811	

*Only consider adults as evacuees (persons under 18 years old is not considered).

From Table 4.5, it was shown that the estimates of spouse gathering is 458,689, accounting for 49% of married-couple families, which is consistent with the finding from the interviews that of married-couple families, 44% would conduct the action of gathering a spouse. Table 4.5 also displays that in total, 1,661,817 persons would return home to gather family members in Scenario #2, and belong to 1,117,158 households which occupy 86% of evacuation-involved family households. According to the estimates, the average number of adults (per household) returning home is 1.49. As in the interviews, approximately 90% of households are family households; this proportion is higher than the distribution of household structures in the Census. Oversampling family households is a means of fulfilling the study objectives aiming to investigate the behavior of family gathering in an incident. In order to comply with this oversampling, the home-gathering model is applied to the subset of family households, by which it was found that the number of home-gathering is 68% of family households. Mode shares of home-gathering (see Table 4.5) imply that modes of transportation do not affect this gathering behavior much; family members could take whatever mode they use to leave from home to return home. Estimated mode shares of spouse-gathering leans towards the mode of driving alone, occupying 98% of the total trips.

Table 4.5. Number of Synthetic Persons, Households and Trips for Incident Scenario #2

			# of Persons		# of Trips	
			Number	Percent	Number	Percent
Baseline	Drive alone		2,372,130	69.6%	2,372,130	69.6%
	By transit		461,382	13.5%	461,382	13.5%
	Carpool		572,903	16.8%	572,903	16.8%
	Total		3,406,415		3,406,415	
Child pick-up	Drive alone	Child pickup	793,743	22.5%	1,774,798	39.3%
		Non-pickup	1,862,120	52.7%	1,862,120	41.3%
	By transit	Child pickup	0	0.0%	0	0.0%
		Non-pickup	391,878	11.1%	391,878	8.7%
	Carpool	Child pickup	0	0.0%	0	0.0%
		Non-pickup	484,343	13.7%	484,343	10.7%
	Total		3,532,084		4,513,139	
Home-gather*	Drive alone		977,222	70.7%	-	-
	By transit		122,384	8.8%	-	-
	Carpool		283,522	20.5%	-	-
	Total		1,383,128		-	-
Spouse-gather	Drive alone		449,273	97.9%	-	-
	By transit		2,171	0.5%	-	-
	Carpool		7,245	1.6%	-	-
	Total		458,689		-	-

*Home-gather is only applied to family households.

In summary, the household gathering related demand model is reasonable and consistent with the interviews. The demand model has not been applied to other geographic areas, in other words, it has not been calibrated with another set of data. The transferability of this demand model is a further direction like many other activity-based demand modeling efforts. However, the framework of integrating a behavior analysis with a traditional network modeling can be transferred and is a major contribution to the evacuation field, as are the estimated evacuation chains achieved through this case study.

Network Modeling

The CMAP model simply adopted the BPR functions to calculate link travel time; different parameters were used for different types of roads (especially freeways and arterial roads). Calibrations of BPR function parameters were conducted in VISUM for the mid-day period; by comparing the estimated traffic volumes with CMAP modeled volumes (shown in Figure 4.5). It should be noted that the volume-delay functions were directly used to represent an evacuation situation, and no toll is considered in an emergency.
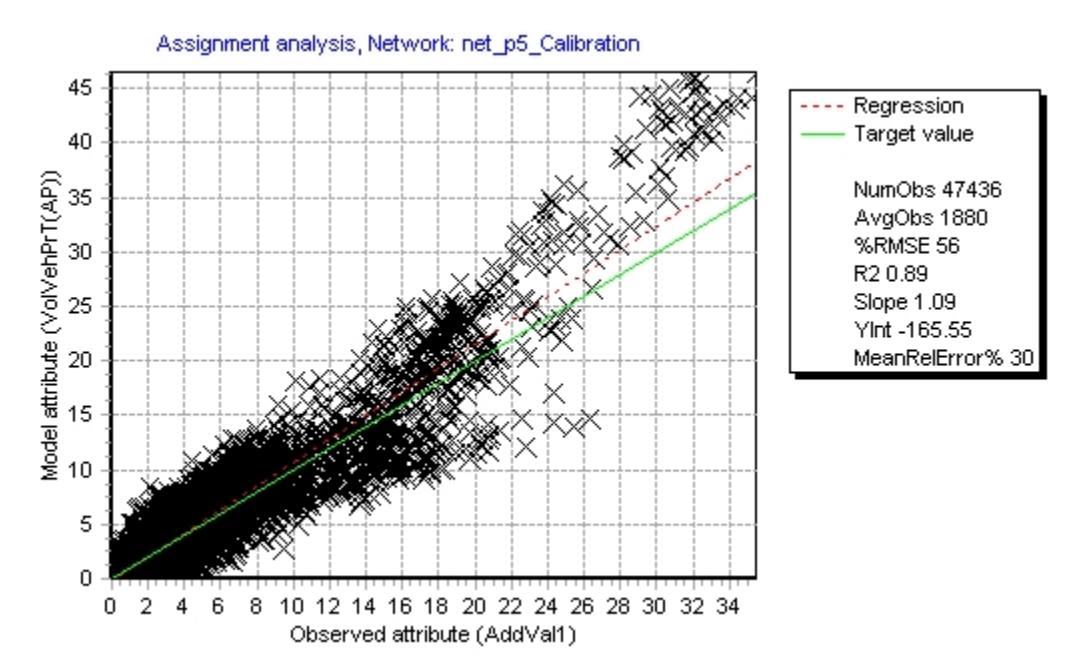
Figure 4.5. Comparison of VISUM Estimated Volumes with CMAP Modeled Volumes

*Observed attribute of x-axis refers to the CMAP modeled volumes; model attribute of y-axis refers to the VISUM estimated volumes. The figure is generated by VISUM.

The generated trip chains were assigned to the network using PTV VISUM. First, individual evacuation-chains are broken into several trips, and departure times of each trip are estimated based on zonal travel time outputted from VISUM. The whole simulation period is divided into time intervals of equal length (15-min), origin-destination demand was then generated for each time interval and assigned to the network by a VISUM built-in assignment method, dynamic user equilibrium (which is part of the standard VISUM package, and with the implied assumption that sufficient information on road conditions is available to all drivers during the evacuation). VISUM has another dynamic assignment method, dynamic stochastic assignment, which is not able to handle the size of the network. In contrast to static assignment where departure time of a trip is ignored, dynamic assignment accounts for departure time of a trip by including time windows. The modeling period is divided into several time slices, so that both spatial and temporal connections between links can be taken into consideration during an assignment. In addition, assignment also considers queue spillback effects. As time-dependent characteristics of evacuation demand are essential to modeling evacuation situations, the

dynamic assignment is necessary and ideal for this study. Departure time of subsequent trips cannot be estimated accurately based on travel time estimates in normal situations, so iterations have to run between running dynamic assignment and breaking evacuation chains to trips; in this sample application, iterations run three times. The mean absolute error of number of trips in each time interval is 4.8% after three iterations.

The total simulation time was set to be 6 hours for Scenario #1 and 20 hours for Scenario #2. Incidents are assumed to occur at time 0; network performance is analyzed after the 1st hour. Normal midday traffic of half an hour was loaded to the network as background traffic and distributed through an hour by proportion of 40%, 30%, 20% and 10% for each 15-min time interval of the first hour of the modeling period. The arbitrary predefinition of background traffic stems from treating all people inside the dangerous zone as evacuees and generating them separately, so background traffic here only refers to the vehicles traveling on the network at the moment of occurrence of incidents, and most of these travelers will be loaded to the network later as evacuees. As the CMAP model revealed that average travel time for the midday period is 30 minutes, it is reasonable to assume that only 30-minute traffic is involved as background traffic.

Evacuees Leaving the Dangerous Area
Cumulative percentages of evacuees leaving the dangerous area by time intervals, as illustrated in Figure 4.6, were used to evaluate evacuation-related performance. Figure 4.6 (a) shows that at the 4th hour after the occurrence of a minor incident, 98% of evacuees have left the 5-mile dangerous area for the baseline case, the value is 95% when considering child pick-up activities. From Figure 4.6 (b), at the 10th hour after the occurrence of a major incident, of all evacuees, 49% can leave 25-mile radius risky area for the baseline case, and 39% does so for the gathering case; the values are 61% and 45% at the 15th hour, and 64% and 47% at the 20th hour. Thus, for a minor incident considering household pick-up activities slightly reduces the proportions of evacuees that can leave the impacted area by each time interval, and for a major incident, the reduction tends to be significant. This result also implies that the baseline scenario without considering child pick-up behavior shows faster network clearance than scenarios with gathering.
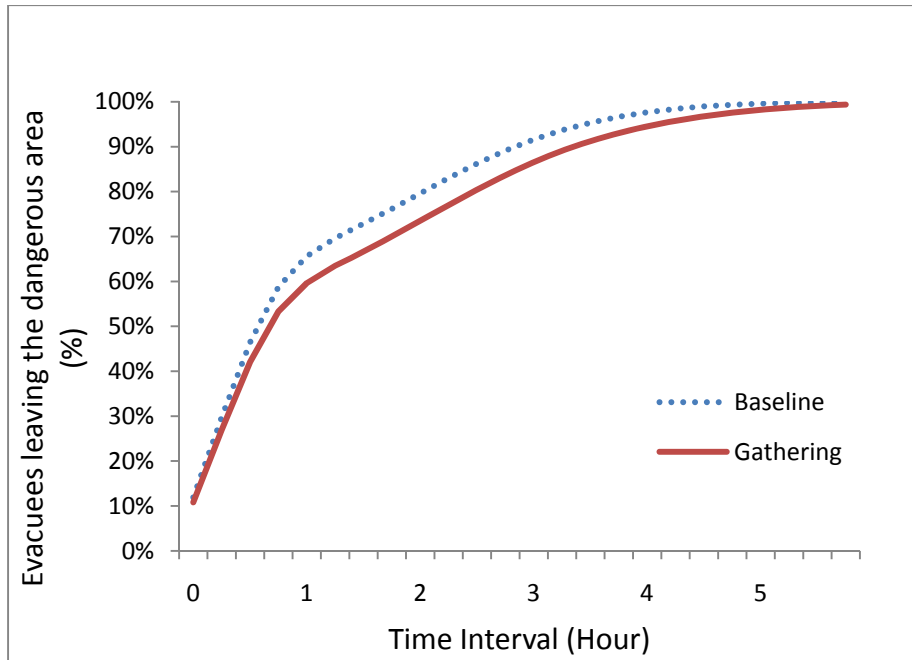
(a) Scenario #1
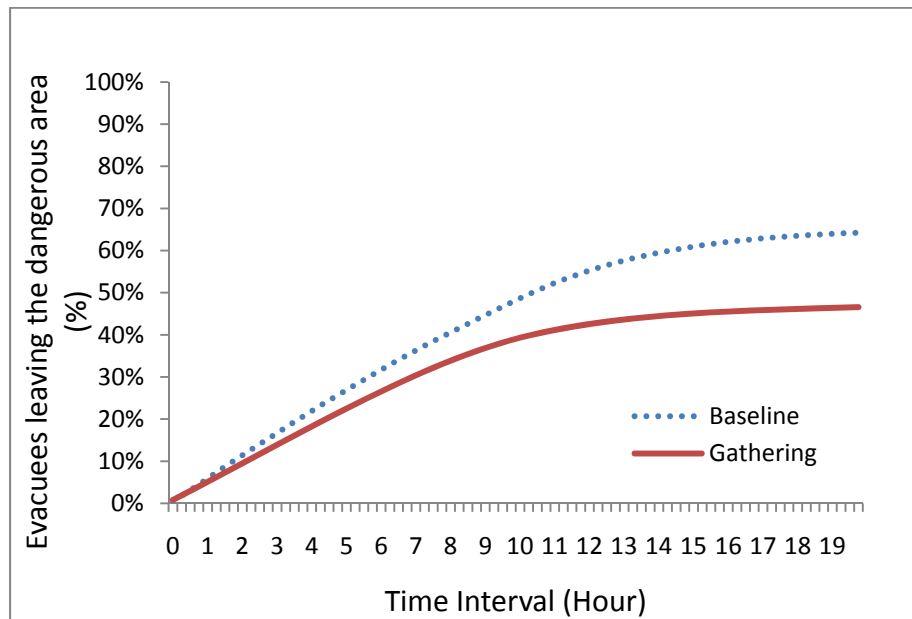
(b) Scenario #2

Figure 4.6. Cumulative Percentages of Evacuees Leaving the Dangerous Area

Vehicle Hours Traveled (VHT)

Overall network performance is evaluated by total vehicle hours traveled (VHT) on the network (at estimated link speed in each time interval). Figure 4.7 displays VHT for Scenario #1, and implies that with child pick-up considered, VHT on the network greatly increases. Figure 4.8 illustrates total vehicles heading to/from the impacted area in each time interval through the predefined boundary of the area. Figure 4.8 clearly shows that vehicle volumes to/from the impacted area increase when child pick-up behavior is considered. As child pick-up behavior adds more traffic to the network (e.g., parents outside dangerous areas heading to schools within dangerous areas to gather children), average travel time over the network for the gathering case only slightly increases compared to the baseline case, which implies that child pick-up behavior slightly deteriorates overall network performance compared to the baseline case.
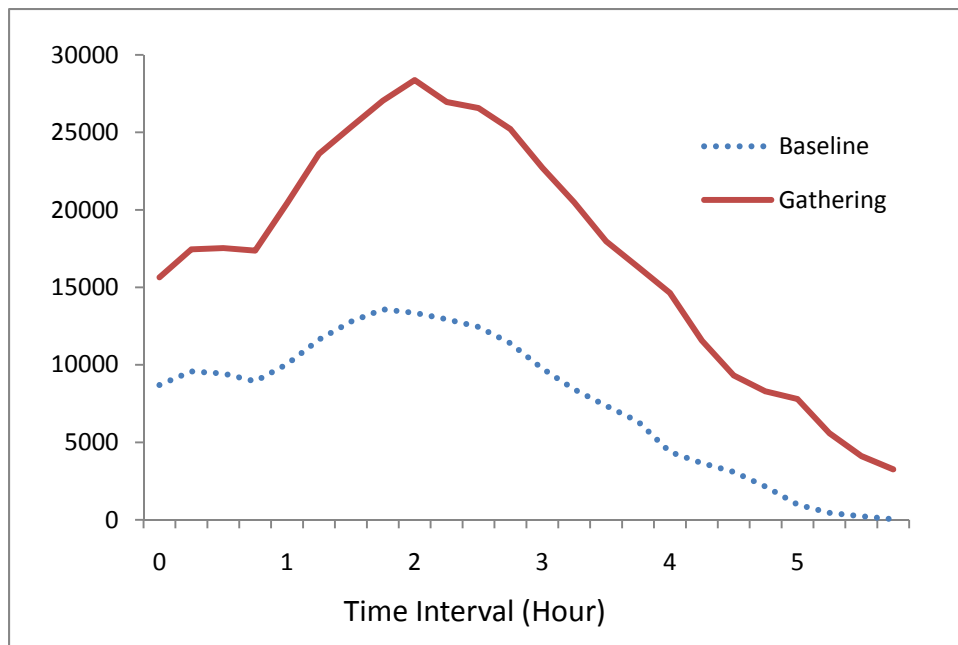
Figure 4.7. Total Vehicle Hours Traveled on the Network (Scenario #1)
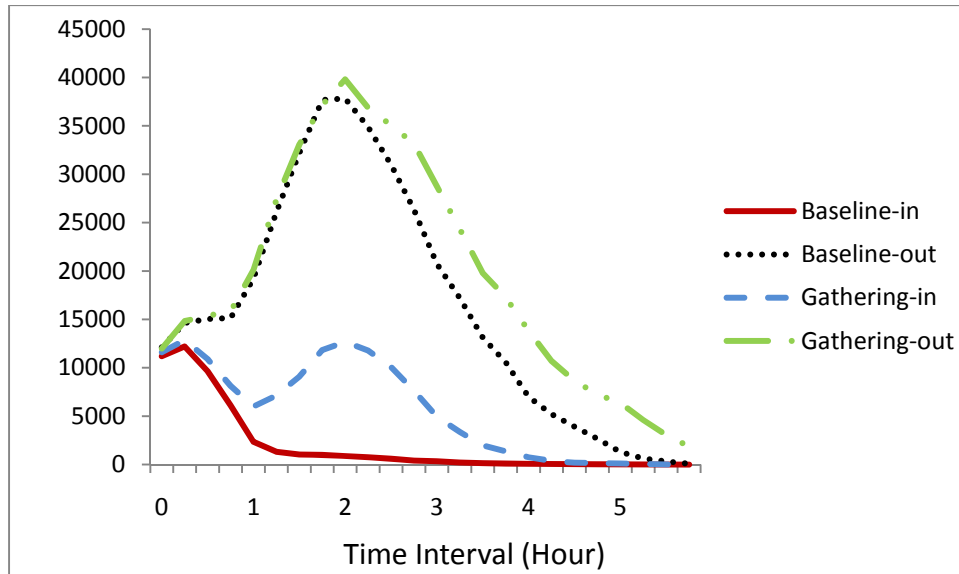
Figure 4.8. Total Vehicle Volumes To/From the Impacted Area (Scenario #1)

Scenario#2 involves a large evacuation radius, 25 miles. In order to further investigate overall network performance on the entire area, the overall network is analyzed on the levels of five evacuations radii, 5, 10, 15, 20 and 25 miles, as shown in Figure 4.9. Figure 4.9 illustrates that in most cases, considering family-gathering behavior decreases VHT. Since family-gathering adds more intermediate trips and has time where vehicles are out of the network for pick up activities, the conclusion can be drawn that average travel time on the network reduces when considering family-gathering behavior. However, recall that the number of vehicles completing the evacuation is substantially smaller for the gathering case.

Figure 4.9 displays that the 15-mile radius area shows different patterns from other radii in terms of VHT: the associated VHT for the gathering case is higher than the VHT for the baseline case. By investigating total vehicle volumes on the areas, we found that for the areas with the radius lower than 15 miles, the difference of average travel time with and without considering family-gathering behavior is quite slight and tends to fluctuate between positive and negative over time intervals, while for the 20 and 25-mile radius areas, the reduction of average travel time is quite significant, implying that family-gathering alleviates network congestion for a large-area evacuation situations, likely due to time spent picking up family members.
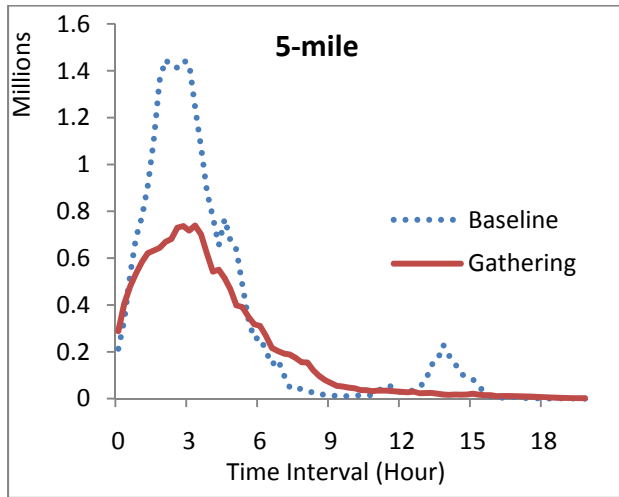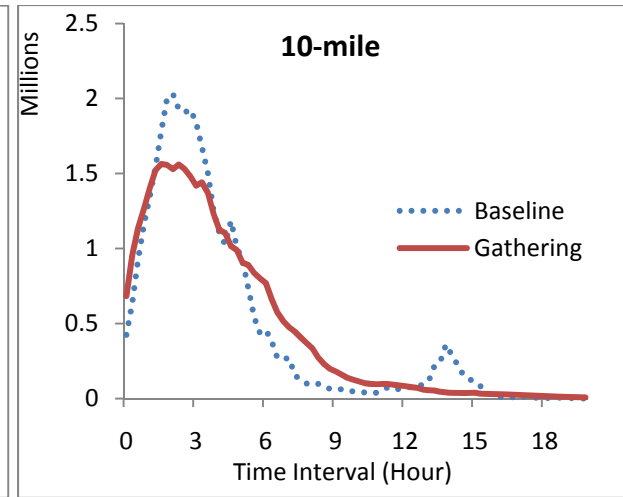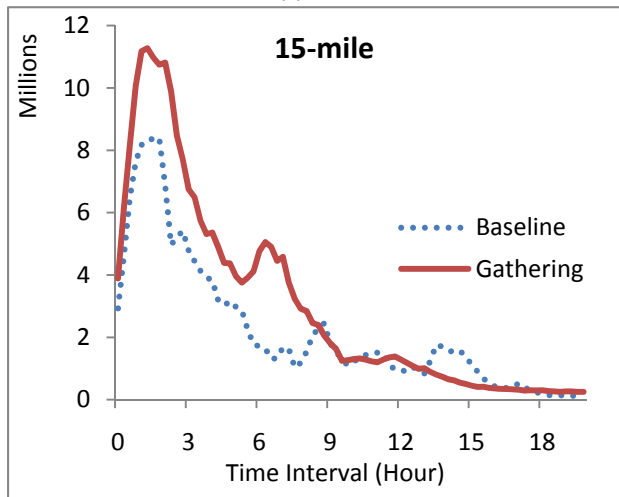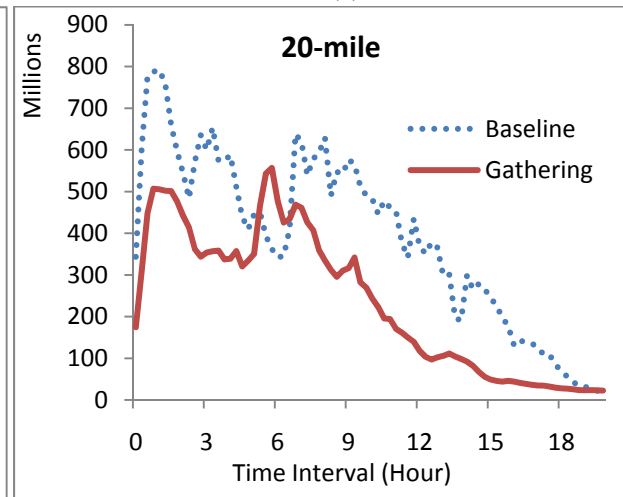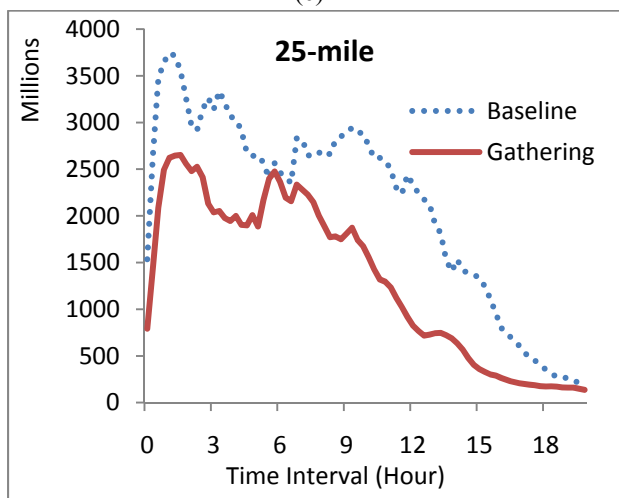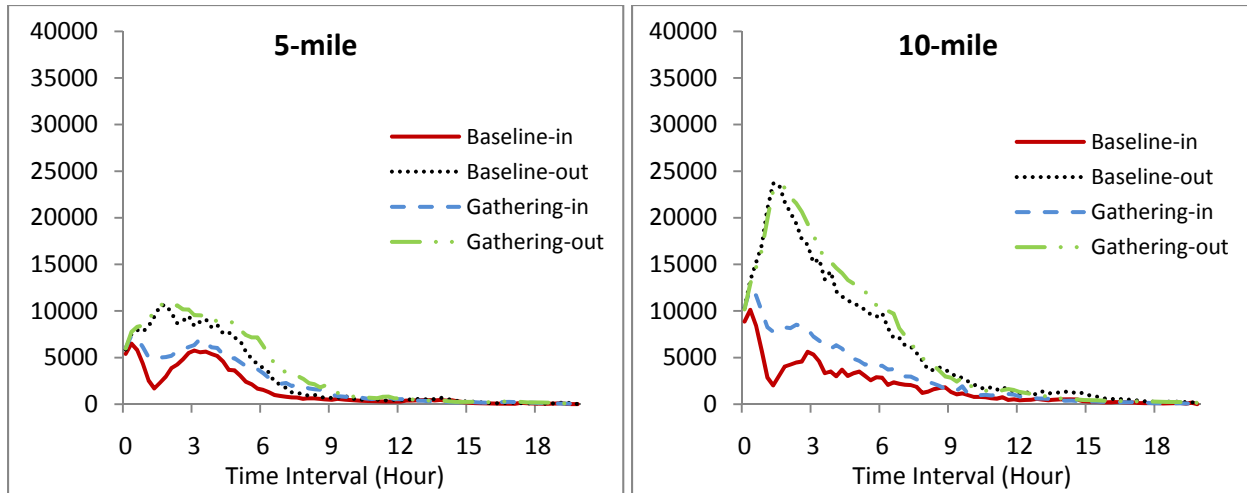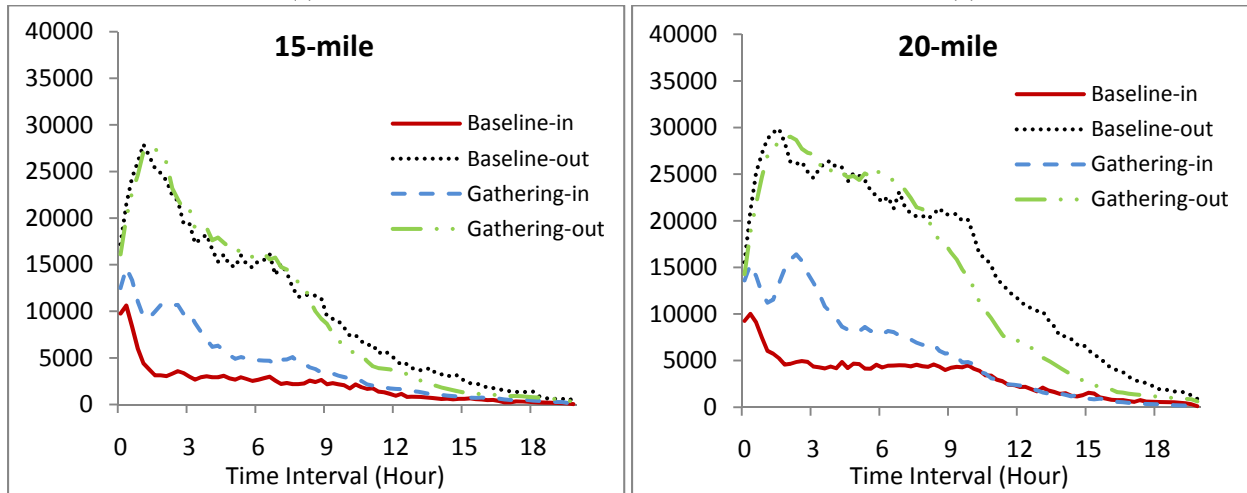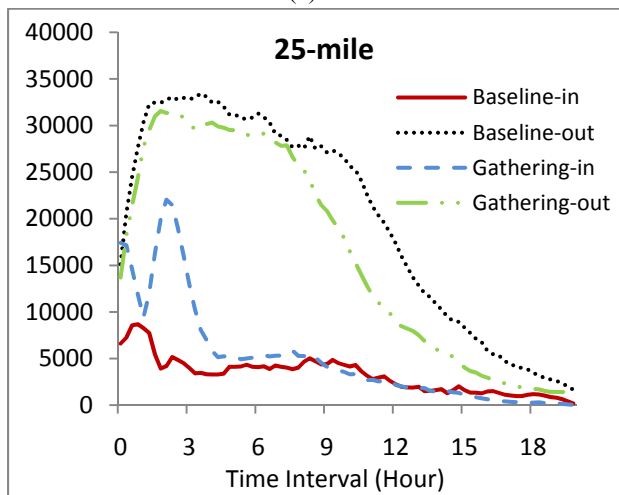
Figure 4.9. Total Vehicle Hours Traveled on the Network (Scenario #2)

Figure 4.10. Total Vehicle Volumes To/From the Impacted Area (Scenario #2)

Figure 4.10 shows total vehicle volumes to/from the impacted areas with five evacuation radii in each time interval; this figure illustrates the shifts of demand by household-gathering spatially and temporally. Family-gathering increases number of vehicles heading into each area because of people heading in the "wrong" direction to gather family members, but decreases vehicle volumes leaving the areas with large evacuation radii, e.g., 20 miles and 25 miles, because it takes longer to unite with family than just evacuate themselves.
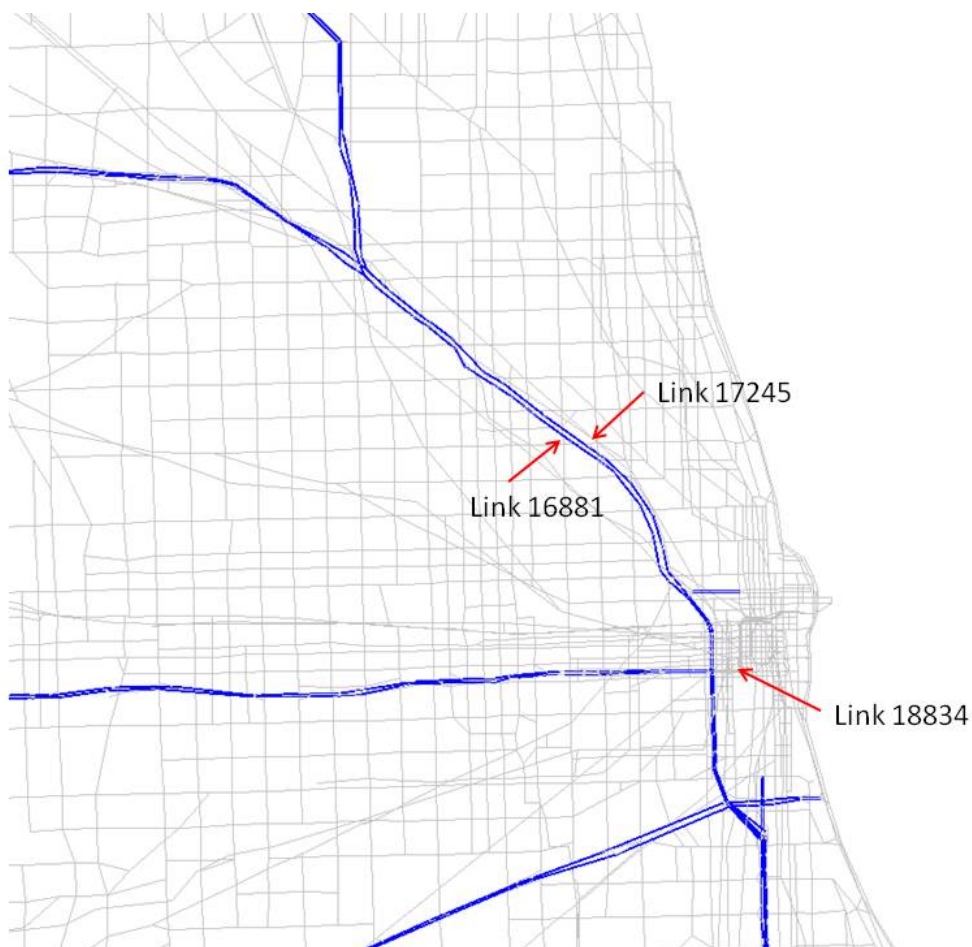

Figure 4.11. Locations of Three Selected Links for Further Analysis

VHT was further investigated for specific links shown in Figure 4.11. Figures 4.12(a)-(c) illustrate vehicle hours traveled on three links for two cases for Scenario #2. Link 18834 is located near the boundary of the downtown area with the direction of leaving downtown, Link 17245 is located on a freeway going northwest from downtown; Link 16881 is located near Link 17245 with the opposite direction. Links 18834 and 17245 are with the direction of main evacuation flow, while Link 16881 is in the opposite direction. Figures 4.12(a)-(b) show that in

the case where household gathering behavior is considered, vehicle hours traveled on the links in the evacuation direction significantly increase; for Link 17245, both the number of vehicles on the links and travel time on the links increase. Figure 4.12(c) illustrates that in the opposite direction of main evacuation flow, vehicle hours traveled increase, reflecting that evacuees go to other places to gather with family rather than leaving the dangerous area directly.
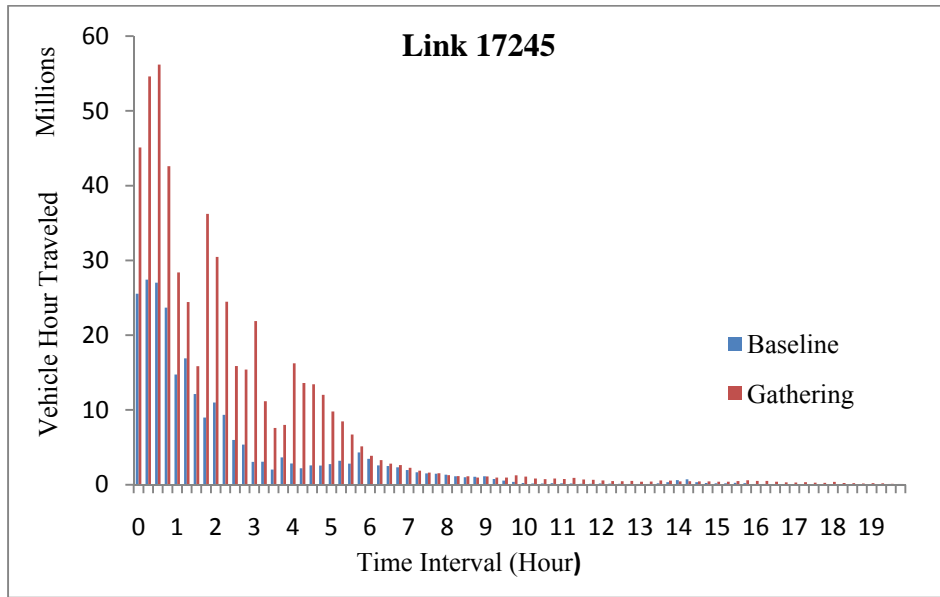
(a) Link 17245
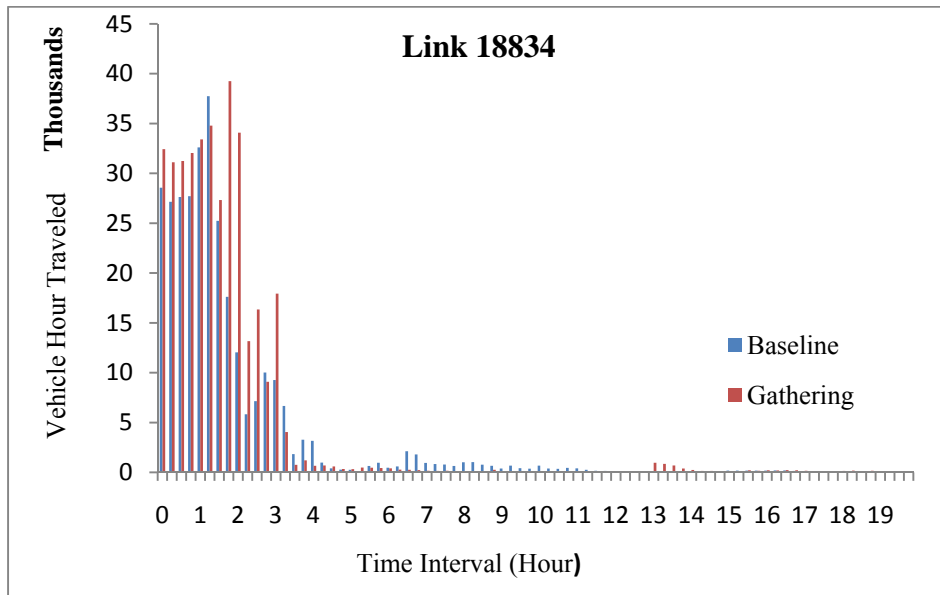
(b) Link 18834
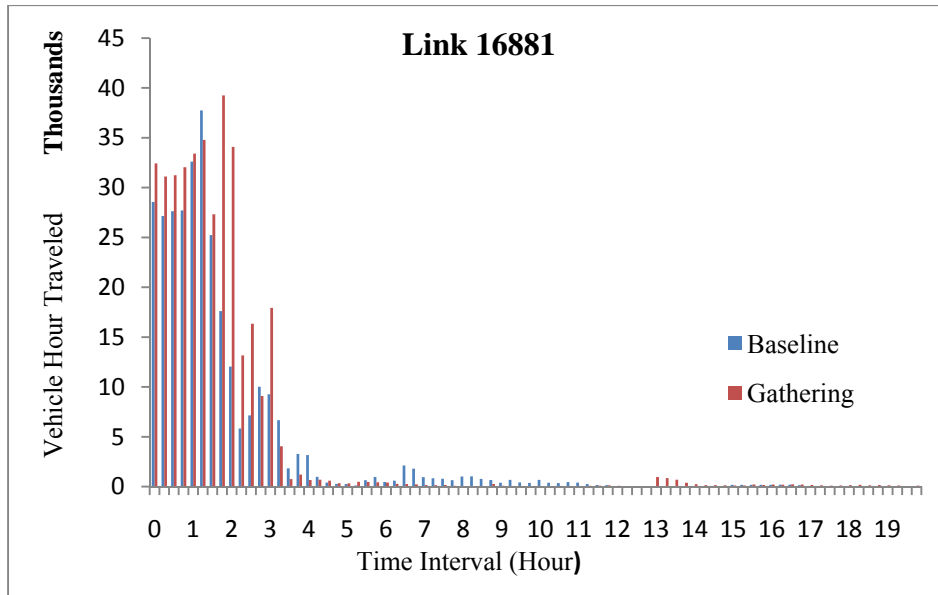
(c) Link 16881

Figure 4.12. Vehicle Hours Traveled on Links 17245, 18834 and 16881 (Scenario #2)

Sensitivity Analysis

A flatter departure time distribution (a sigmoid curve with $T= 5$ and $\alpha =.75$, as shown in Figure 4.13) is investigated for Scenario #2 as a sensitivity analysis. Figure 4.14 displays percentages of evacuees leaving the dangerous area: of all evacuees, 48% can reach the safe zones by the 10th hour after the occurrence of an incident without family-gathering considered; when considering family-gathering 40% can reach the safe zones. The numbers are 64% and 51% by the 15th hour, and 71% and 54% by the 20th hour. Compared with the simulations that departure time follows the sigmoid curve of $T=2$ and $\alpha =2.5$, we found that flatter departure time can lead to more efficient evacuations. This finding supports the potential effectiveness of phased evacuations (when safe to do so) and leads to some useful policy implications. For instance, since departure time is significant to evacuation efficiency, certain strategies could be adopted by emergency officers to guide the departure time of evacuees, such as educating people that later departures may achieve quicker evacuations, although compliance remains a practical issue to be addressed in the future.
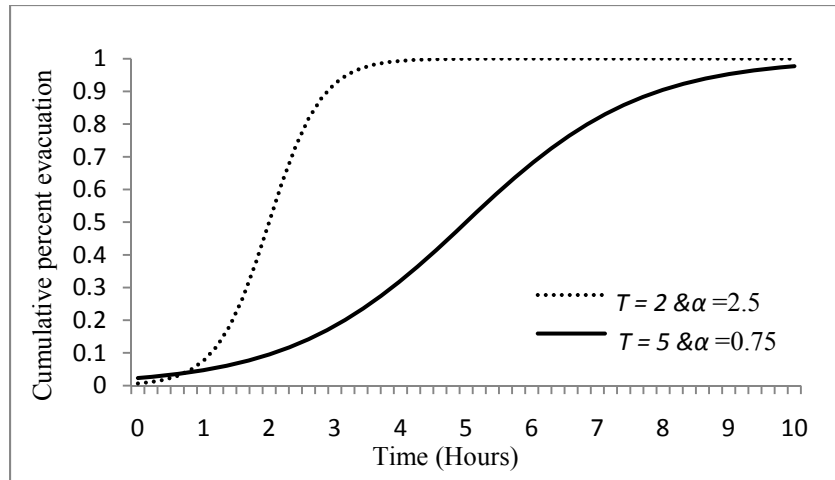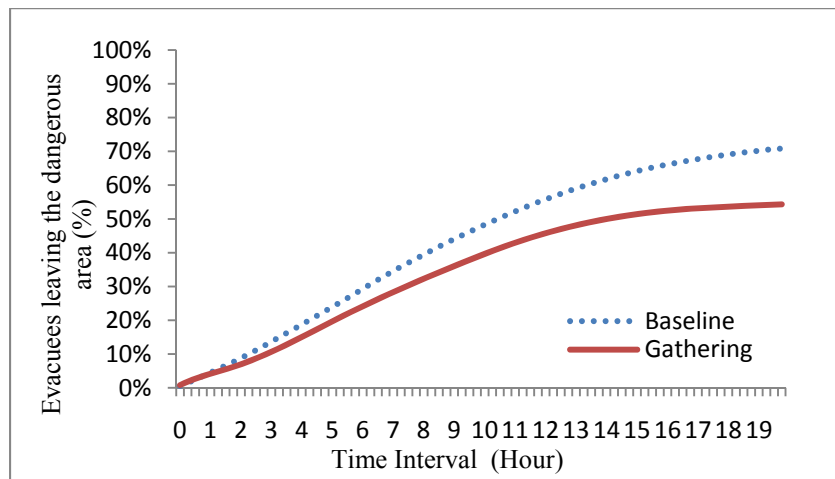
Figure 4.13. Two Departure Time Distributions

Figure 4.14. Cumulative Percentages of Evacuees Leaving the Dangerous Area (Scenario #2, $T= 5$ and $\alpha =.75$)

Figure 4.15 displays VHT for five areas with the radii of 5-25 miles. Figure 4.16 displays total vehicle volumes to/from the areas. VHT shows relatively little difference with and without family-gathering considered, implying that average travel time on the network decreases with family-gathering considered (since vehicle volumes are higher for the gathering case than the baseline case), and these differences are not as significant as the case that departure time follows the sigmoid curve of $T = 2$ and $\alpha = 2.5$. The benefits on network performance caused by family-gathering behavior for a large-area evacuation are becoming less significant when departure time for evacuees tends to be distributed more smoothly. Moreover, vehicle volumes to/from five areas appear to have similar patterns with the departure time distribution ($T = 2$ and $\alpha = 2.5$).
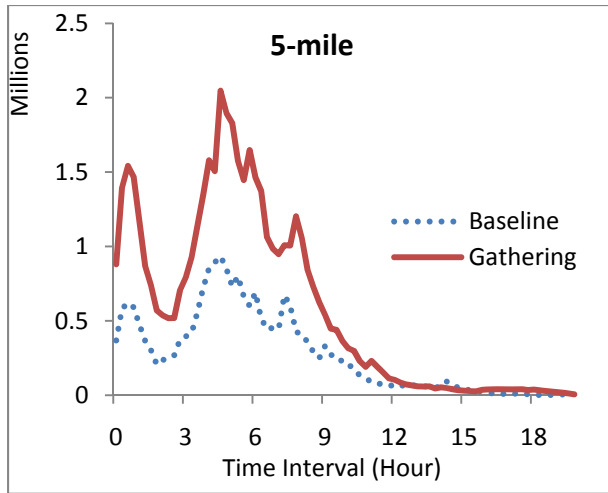
(a)
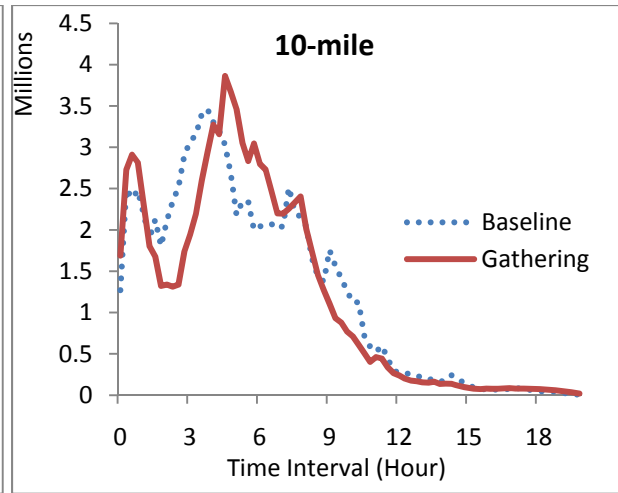
(b)
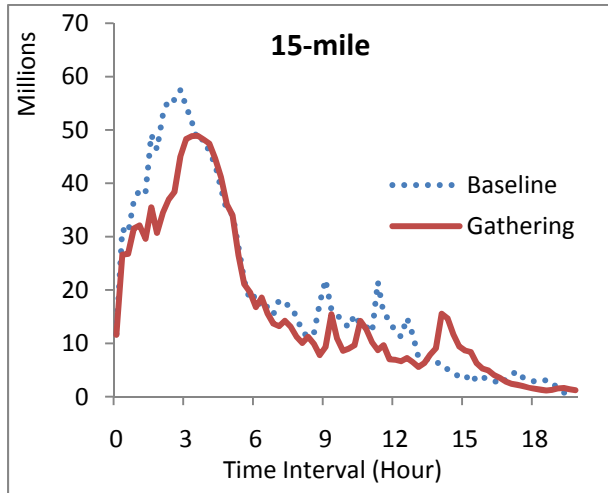
(c)

(d)

(e)

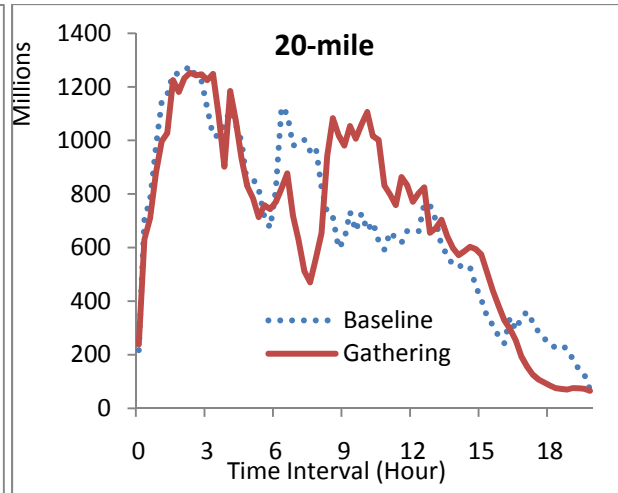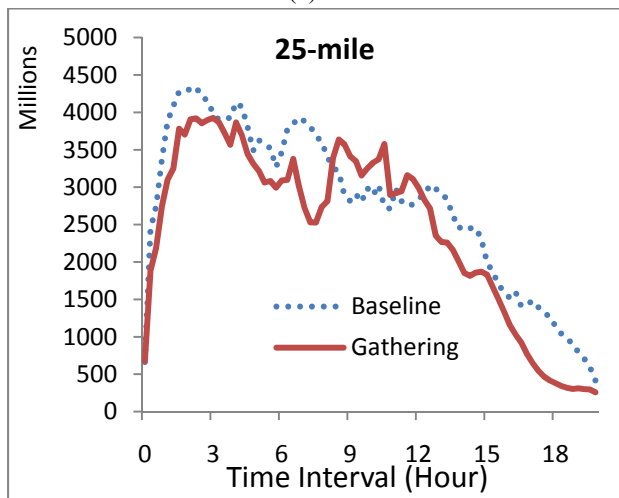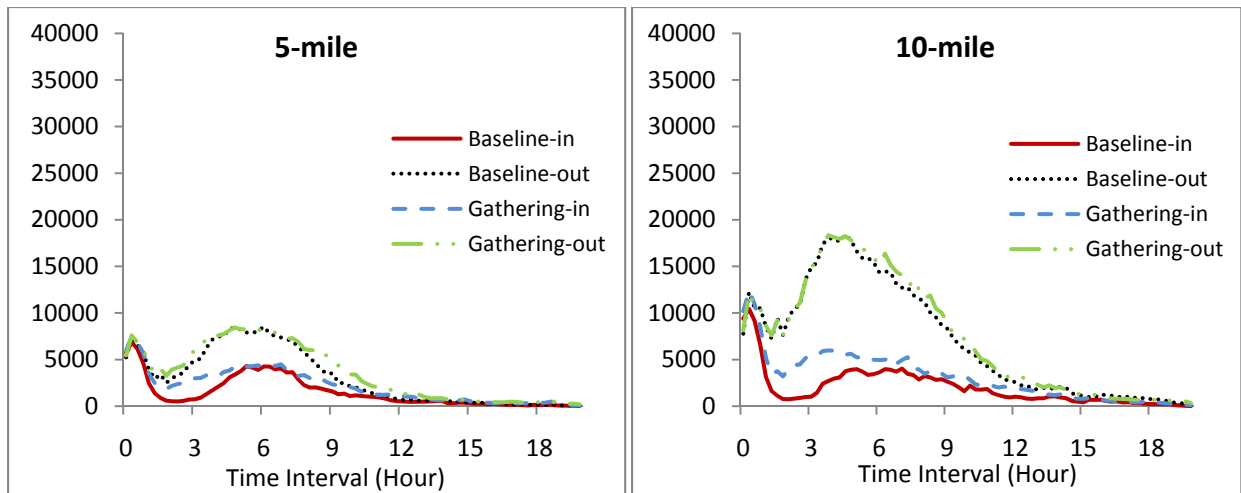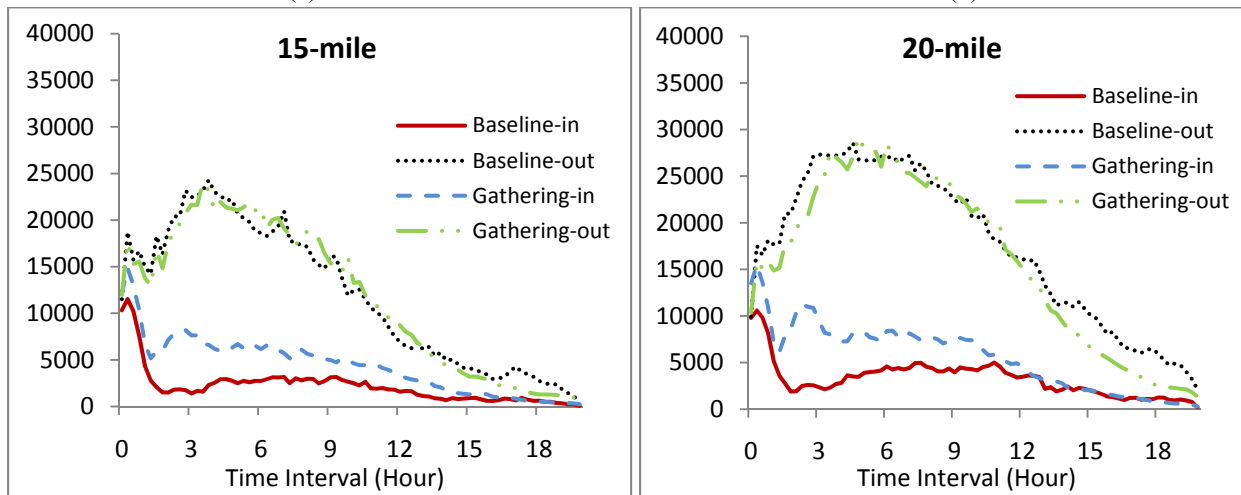Figure 4.15. Total Vehicle Hours Traveled on the Network (Scenario #2, *T*= 5 and *α* =.75)
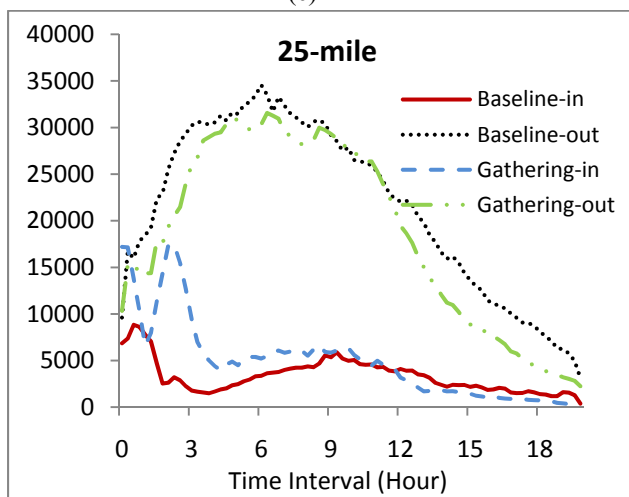
Figure 4.16. Total Vehicle Volumes To/From the Impacted Area (Scenario #2, *T*= 5 and *α* =.75)

Transit Assignment

CMAP also provided the transit network (bus and rail) for the Chicago Metropolitan region including the information of line routes, travel time between stops and headway information for each line. Transit assignment was carried out using the headway-based assignment method provided by VISUM. This method has two shortcomings, 1) it does not deal with time-dependent demand, instead, it assigns all demand to the transit system simultaneously, which means that by summing up the estimated travel time by transit and the estimated departure time of an evacuee, we can have obtain actual evacuation time; 2) it is based on predefined headway information and ignores current traffic conditions of the network, which is not necessarily suitable to model evacuation situations. Therefore, effects of household gathering behavior cannot be readily handled.

However, it still can provide some useful insights to evaluate evacuations by transit. Figure 4.17 illustrates transit assignment for Scenario #1 at 0 and 0.5^{th} hour after the demand are loaded to network; Figure 4.18 displays transit assignment for Scenario #2 at 0 and 1st hour after a disaster's occurrence. From these figures, we can conclude that, for the transit systems with dedicated lanes, evacuation time by transit is approximately less than 1 and 2 hours for Scenario #1 and Scenario #2, respectively.

(a) at 0 Hour   (b) at the 0.5^{th} Hour

Figure 4.17. Transit Assignment for Scenario #1 (Sigmoid Curve of Departure Time - α =2.5, T = 2)
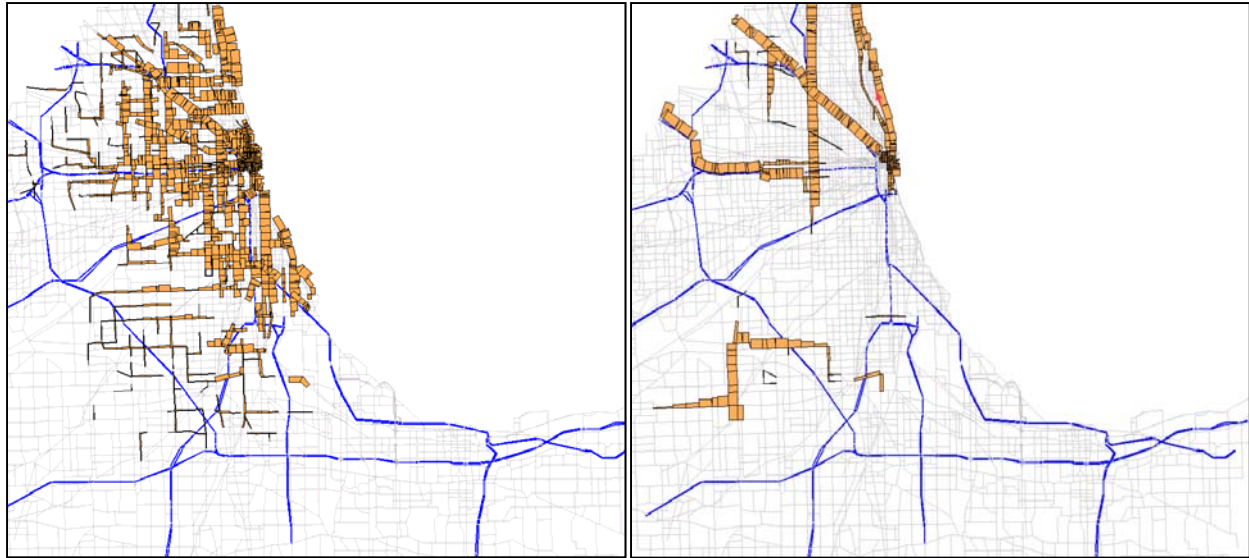
(a) at 0 Hour   (b) at the 1st Hour

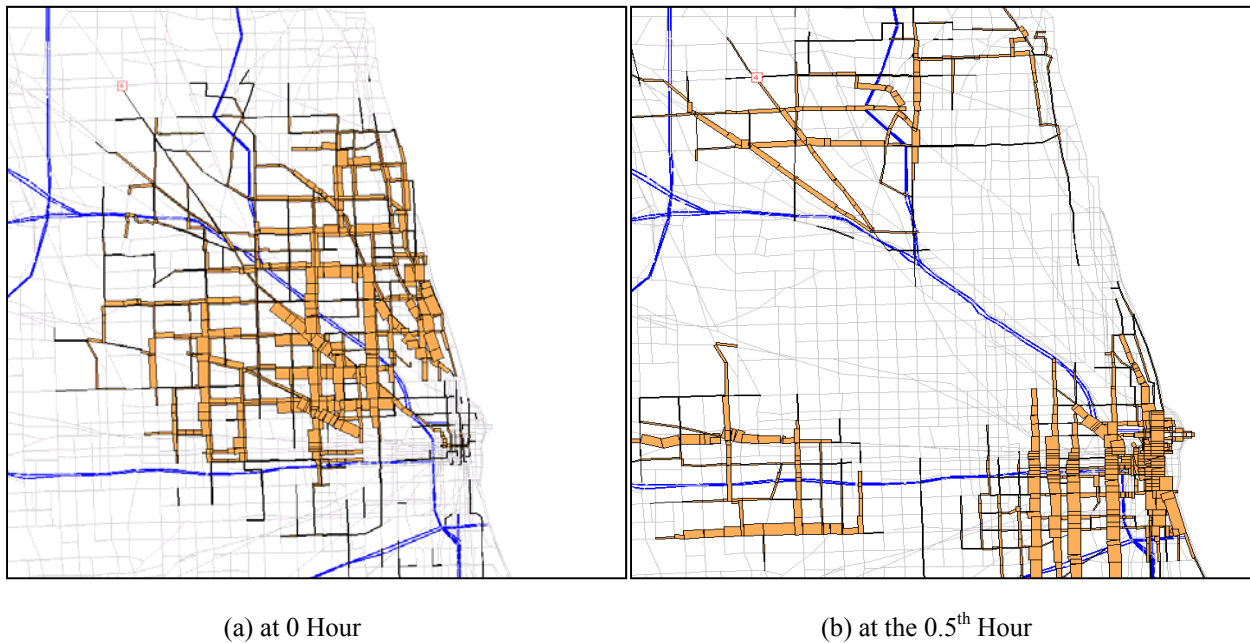Figure 4.18. Transit Assignment for Scenario #2 (Sigmoid Curve of Departure Time - α =2.5, T = 2)

Conclusions

A model framework to integrate human behavior analysis and network assignment modeling was presented in this chapter. The framework follows the traditional four steps: 1) estimate household gathering chains under an evacuation using discrete choice (Logit) model and sequencing chains following the principle of "nearest first", 2) assign directions of destinations ensuring the least travel time to safe zones from the last stop within the hot zones, 3) apply decision tree based mode choice models to determine mode used for evacuation, 4) use dynamic assignment method to assign time-varying demand on the network. The whole framework was tested in the Chicago metropolitan region for two hypothetical incidents with two different extents of consequence, causing 5-mile and 25-mile radius evacuations, respectively. The results showed that considering household gathering behavior will reduce proportions of evacuees who reach safe zones by a certain time period: the reduction is slight for a minor incident and significant for a major incident; while not necessarily deteriorating overall network traffic performance in both incidents. Depending on the time spent at the gathering locations, family gathering activities may alleviate network congestion in a major incident since part of trips are diverted to other roads/directions than major evacuation flows. .

The advantages of the presented framework include: 1) it can be integrated with activity-based transportation planning models that are widely used all over the world, 2) it can be applied

to a large-area evacuation situation, and 3) it can be applied to a multi modal transportation system. Limitations of the sample application include: 1) the behavior model is based on a relatively small interview dataset and the model parameters may not be representative of the whole Chicago metropolitan area, 2) inherent limitations with the mesoscopic simulation package (PTV VISUM) for traffic assignment caused the activity chain to be broken into several OD trips and thereby led to imprecision in departure times for subsequent stops, and 3) even though dynamic assignment is used and queue spillback is considered, since VISUM does not dispatch actual vehicles and it analyzes average performance on roads rather than performance of each individual vehicle, consequently, network clearance time can hardly be estimated precisely. So in the sample application, only conceptual effects of household gathering behavior on network traffic performance can be found, and potential bottlenecks can be identified, but precise network clearance time cannot be readily estimated using VISUM. In the future, other traffic assignment tools which are able to handle both large-scale networks and congestion situations (particularly DynusT, TRANSIMS) should be integrated with the presented chain generation methods.

Chapter 5   Relocating Children in Daytime No-notice Evacuations: Methodology and Applications for Transport Systems of Personal Vehicles and Buses

Abstract

Under no-notice conditions with family members collecting dependents, the geographic location and characteristics (e.g. number of entrances/exits) of these pickup points become crucial factors to efficient evacuation. This paper presents a linear integer mathematical program for facilities to relocate, optimally, dependents that need to be picked up. The program is iterated with a traffic simulation model to obtain an optimal set of locations based on anticipated travel times with dependents relocated to those sites. The entire methodology is applied to a sample network based on Chicago Heights, Illinois with three safety time thresholds. The results indicated that the safe evacuation time threshold is important to the relocation strategy. When the safe evacuation threshold is adequate, relocating dependents of facilities increases the number of successful evacuees and increases average travel speed of the total network; it also significantly benefits those who rely on public transit to evacuate because new sites are closer to bus stops and walking times to stops are reduced. Application of the proposed methodology can assist local decision-makers to take effective measures during no-notice evacuation and the relocation sites could be part of local evacuation management plans.

Introduction

No-notice events occur at unpredictable times and locations, usually have instant and severe consequences, and may require immediate evacuation. Facilities like senior or daycare centers and schools, where dependents are located during the day, are potential bottlenecks for daytime evacuations. These dependents, including elderly relatives and children, lack direct access to personal transportation and may have to wait for caregivers to collect them for transport to a final

household evacuation destination. Large numbers of drivers rushing into these places to pick up their dependents may create bottlenecks, slow the traffic of surrounding areas, or worsen congestion that was already severe due to the surge of other evacuees. Thus, the locations of these pickup points become a crucial factor to efficient no-notice evacuations. Optimal pickup locations could eliminate unnecessary bottlenecks and decrease evacuation time. Original facility locations are not necessarily ideal because they are not designed for emergencies and limited entry/exit by itself may be a bottleneck. Therefore, it is important to determine more accessible sites to which facilities can move dependents in order to facilitate their collection and evacuation in general.

Liu and Murray-Tuite (2008) studied the potential of relocating family dependents to more accessible sites, considering only personal vehicles. However, according to the U.S. Census, in large cities, such as Chicago, New York, and Miami, more than 25% of households do not have private cars and rely on public transit (U.S. Census Bureau, 2000). The carless population's evacuation needs received comparatively little attention until Hurricane Katrina (Renne et al., 2008). In 2006, the U.S. Department of Homeland Security reported that very few cities had evacuation plans for those without cars (U.S. Department of Homeland Security, 2006).

This paper considers both private vehicles and buses to find an optimal relocation site for each facility. This manuscript presents a mathematical program and solution technique involving an optimization-simulation iteration process to select the relocation sites. A logit mode choice model determines the probability that a certain mode is chosen. Changes in many factors such as safe evacuation time and evacuation demand may lead to different optimal relocation sites. Therefore, this study examined multiple scenarios (i.e., with and without mode shifts) and cases (i.e., different factors such as safe evacuation time thresholds), and based on these results, more stable relocation sites are recommended for the facilities.

The remainder of this paper is organized into five sections. The first presents an overview of selected previous studies of evacuation behavior and modeling and related location problems. Then a linear, integer program is provided and the solution process, involving iterations between this optimization model and a traffic simulation model is explained. Next, sample applications based in Chicago Heights are analyzed with several demand scenarios. Finally, conclusions and future directions are presented.

Literature Review

Several studies of human response to disasters and household behavior in evacuation found that some demographic and socio-economic factors, such as gender, race, household income, family size, housing type, and elders or children in a household, affect hurricane evacuation decisions (Baker, 1991; Gladwin & Peacock, 1997; Whitehead et al., 2000). Other studies found that households are the basic unit in evacuation: individual decision-makers tend to make household decisions together and allocate roles and responsibilities based on household characteristics. Households that are scattered when an evacuation order is issued will likely gather dependents before leaving the dangerous area (Tierney et al., 2001). Ignoring this gathering behavior leads to errors in modeling aggregate behavior, including overly optimistic evacuation time estimates (Murray-Tuite & Mahmassani, 2003; Murray-Tuite & Mahmassani, 2004).

Though social scientists have studied individual behavior during evacuations, their findings about family gathering, gender, or cultural differences were seldom reflected in early transportation evacuation models (e.g. Sheffi et al., 1982; KLD, 1984; Hobeika & Jamei, 1985; Han, 1990). A few studies partially bridged the gap between individual behavior and network evacuation. Stern and Sinuany-Stern (1989) were among the first to incorporate behavior-related parameters, including the diffusion time of evacuation instructions and individuals' preparation time, in an urban evacuation model. Later in 1993, they tested the effects of household size, car ownership and intersection traversing time on network clearance time (Sinuany-Stern and Stern, 1993). Sinuany-Stern and Stern's work took households, instead of individual household members, as model agents. However, family members could be scattered throughout the network, especially for a daytime evacuation. Murray-Tuite and Mahmassani explored family gathering and pick-up behavior through a household trip-chaining model with two linear integer programs that determined optimal meeting points and pick up sequences and later incorporated this household model with the traffic assignment simulation tool DYNASMART-P (Murray-Tuite & Mahmassani, 2003; Murray-Tuite & Mahmassani, 2004). The present paper further connects individual behavior and network evacuation performance.

This paper also argues that facilities' spatial features, including location and number of entry/exit points, affect evacuation efficiency. This argument is supported by Cova and his associates' previous work. Church and Cova (2000) indicated that evacuating small areas or

neighborhoods may be difficult due to high ratios of population to exit capacity. Cova and Johnson (2002) showed that a secondary exit for a fire-prone canyon community would save households' travel times to different extents depending on the household's location.

These prior results inform the analysis presented here. This manuscript constructs a conceptual model of the household evacuation decision conditioned on the responsibilities of caregivers to dependents. The model presented also incorporates the public transit system along with private cars in a no-notice evacuation context. As a result, the analysis here addresses a significant gap in research and public policy concerning evacuations.

Methodology

An integer program determines optimal relocation sites for facilities by maximizing the total number of successful evacuees with pickup needs (e.g. parents). Facilities refers to schools/daycare centers; relocation sites refer to places that can temporarily accommodate a large number of people, such as parks, churches and city halls, and are not necessarily enclosed areas.

After the formulation presentation, the microscopic simulation model is introduced to provide zonal travel time information for the optimization model. Since the two models interact, iteration between them is performed to achieve the "real" optimal point.

Optimization Model

The notation used in the optimization model is presented in Table 5.1.

Table 5.1. Notation of the Optimization Model

Indices	
i	Index of pickup evacuees' origin nodes
j	Index of pickup evacuees' destination nodes
k	Index of current locations of facilities
l	Index of possible relocation sites for facilities
m	Index of transport modes (bus is indicated by b, car is indicated by c)
a	Index of time interval, a^{th}
Decision variables	
x_{kl}	Binary integer decision variables. $x_{kl} = 1$, if facility k is assigned to site l; 0 otherwise
Model parameters	
S_{ijkl}	Number of successful pickup evacuees who originate from i (or arrive at the network at node i), stop at relocation site l to pick up their dependent (who is originally located in facility k) and evacuate to j, within a safe evacuation time threshold
$q_{ijk}^{a,m}$	Number of pickup evacuees who originate from i at time interval a (or arrive at the network at i at time interval a), have a dependent at facility k to be picked up, and evacuate to j by mode m
A_{ijkl}^{m}	The last time interval during which successful evacuation can be ensured for pickup evacuees who originate from i (or arrive at the network at i), stop at relocation site l to pick up their dependent (who is originally located in facility k) and evacuate to j by mode m
Φ	Average number of dependents a pickup evacuee gathers at a facility
c_l	Capacity of relocation site l (in persons)
d_{kl}	Distance from facility k to relocation site l
f_{kl}	Indicator of whether a major road lies between k and l. f_{kl}=1 if no main streets lie between k and l; 0, otherwise
Y_{ijkl}^{a}	Binary integer variables. Y_{ijkl}^{a}=1, if pickup evacuees who originate from i at time interval a, stop at relocation site l to pick up their dependent (who is originally located in facility k) and evacuate to j, shift their modes from car to bus; 0, otherwise.

The optimization model maximizes the number of successful pickup evacuees by all transportation modes within a certain time threshold, as shown in Equation (1). Pickup evacuees are people with a need to collect dependents inside the dangerous zone, such as parents who pick up their children at schools or daycare centers. Dependents are inside the affected zone, but pickup evacuees may be either inside or outside that area.

$$\max Z = \sum_i \sum_j \sum_l \sum_k S_{ijkl} \tag{1}$$

where,

$$S_{ijkl} = \sum_m \sum_{a=0}^{A_{ijkl}^m} q_{ijk}^{a,m} x_{kl} \qquad \forall i,j,k,l \tag{1-1}$$

subject to:

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$$\sum_i \sum_j \sum_k \sum_a \phi \left(\sum_m q_{ijk}^{a,m} \right) x_{kl} - c_l \leq 0 \qquad \forall l \tag{2}$$

$$(d_{kl} - 0.5)x_{kl} \leq 0 \qquad \forall k,l \tag{3}$$

$$\sum_l x_{kl} = 1 \qquad \forall k \tag{4}$$

$$x_{kl} - f_{kl} \leq 0 \qquad \forall k,l \tag{5}$$

$$x_{kl} \in \{0,1\} \qquad \forall k,l \tag{6}$$

Equation (1-1) indicates that the total number of successful pickup evacuees, S_{ijkl}, is the summation of successful pickup evacuees by each mode, for the time intervals that can ensure successful evacuation. Equation (2) requires the number of dependents relocated to site l to not exceed facility l's capacity. The average number of dependents for a pickup evacuee is assumed to be the same over the facilities. Multiple intermediate stops are not considered in this study; parents who have more than one dependent are assumed to have them at one facility. Equation (3) restricts the relocation site to a walkable distance (0.5 miles) from the original site. Equation (4) guarantees that a facility is assigned to exactly one relocation site. Facilities' current locations are also treated as possible relocation sites. Equation (5) ensures that students do not cross main roads when they are walking to l. The parameter f_{kl} is 1 if no main roads exist between k and l, and 0 otherwise. This constraint ensures students' safety and that they do not slow road traffic and thereby increase evacuation time. Equation (6) restricts the decision variables to binary integers. The optimization model is discrete; time is divided into several intervals, which are treated as a set of integers and associated with a fixed travel cost, (travel time in this study). The linear integer program is solved with the software Lingo 11.0, which can solve linear, nonlinear, and integer programs.

Optimization-Simulation Iterations

The optimization model uses travel time from the simulation model; in reverse, the simulation model is affected by the results of the optimization model. The relocation sites affect road traffic, so the optimal sites may not be truly optimal. To achieve true optimal sets, iteration between the two models needs to be performed until convergence is reached. A procedure to accomplish this iteration process is illustrated in Figure 5.1. The current facility locations are set as the initial

relocation sites. For each iterative run, new relocation sites are found, and the travel time corresponding to those new sites is updated. Iterations continue until convergence is achieved - when optimal relocation sites determined in the current iteration are the same as those found in the last run.

Micro-simulation was chosen to obtain travel time instead of formulating path selections directly, because micro-simulation has the ability to model queues, and reflects the impacts of facilities' entry/exit configuration on travel time, which is crucial for the special case here. VISSIM, part of the PTV VISION traffic analysis package, was used in this study to provide travel time of all paths for each origin-destination pair by car. We assume that pickup evacuees select the path with the lowest travel time.

This paper assumes all evacuees have full knowledge of transit service, including in-vehicle travel time and transit schedules. Thanks to emerging technologies, this assumption is believed to be realistic in the near future in urban areas. VISSIM also outputs travel time for dispatched transit vehicles. Based on this in-vehicle travel time by transit, transit schedules and walking time (from/to transit stations), evacuation time by transit can be obtained. This paper assumes caregivers choose the transit stops/stations with the least evacuation time.
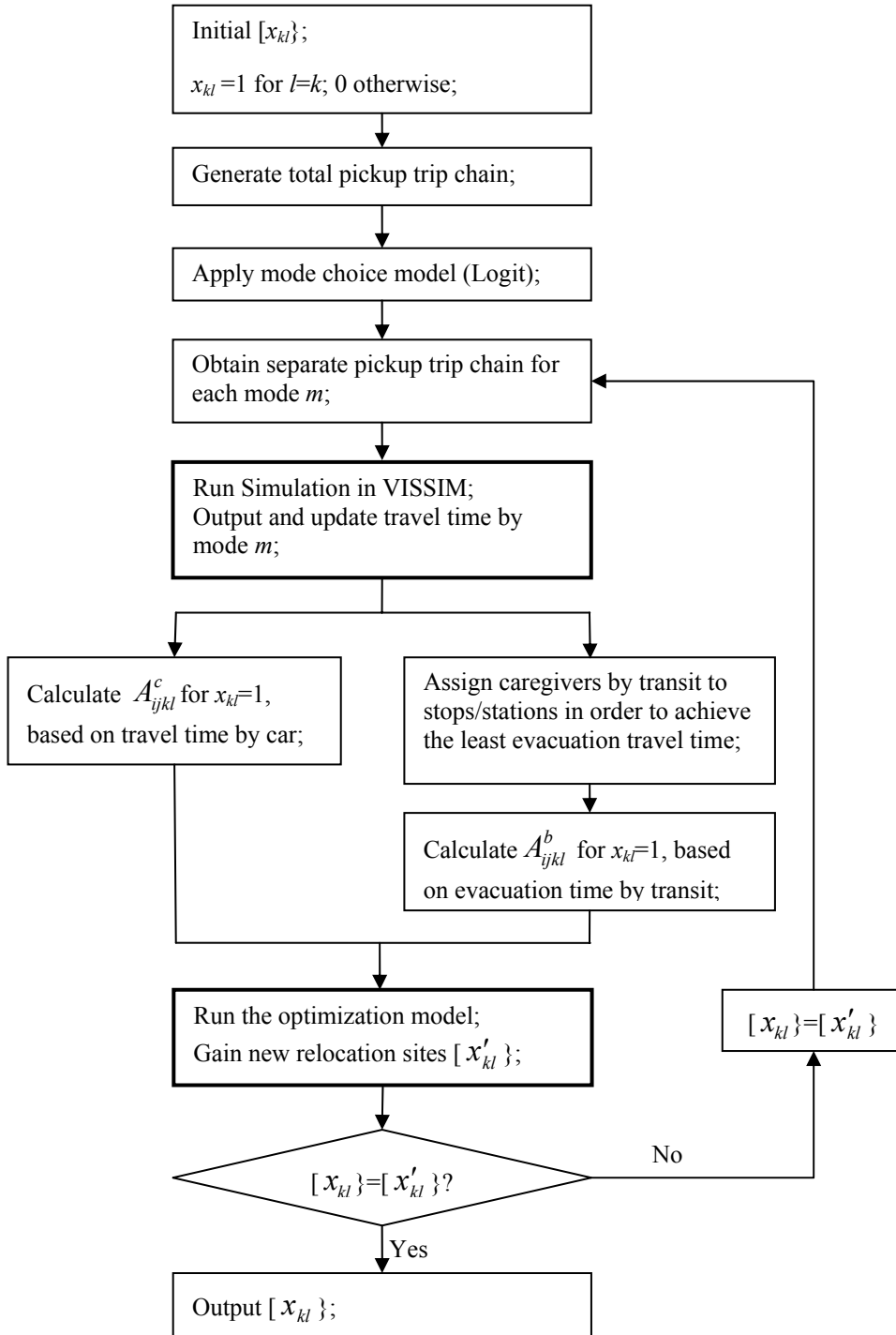
Figure 5.1. Flowchart of the Solution of the Methodology

A logit choice model is used to obtain the probability that a pickup evacuee chooses a given transportation mode. People who choose a certain mode in a normal (baseline) situation are assumed to use the same mode to evacuate. Thus, the mode choice model is applied before

optimization-simulation iteration; once determined, initial mode choices do not change as new relocation sites are found. However, mode shift is considered and modeled within the optimization model as a scenario. In the sample application conducted, only travel time influences mode choice.

A_{ijkl}^{m} is calculated based on travel time from traffic micro-simulation. The calculation guarantees that caregivers starting at time interval A_{ijkl}^{m} by mode m can leave the dangerous zone before a given time threshold and caregivers starting at time interval $A_{ijkl}^{m}+1$ by mode m cannot. Some pickup evacuees may arrive at relocation sites early and have to wait until their dependents arrive. This waiting time is not accounted for in the calculation of A_{ijkl}^{m} and will not affect the result significantly because the optimization model includes a 0.5-mile walking distance constraint, which is a 10-minute walking time constraint if an average walking speed of 3 mph is assumed, and pickup evacuees arriving at relocation sites within 10 minutes after the evacuation starts would be able to evacuate safely.

Sample Application

The sample application is based on Chicago Heights, Cook County, Illinois, about 25 miles from Chicago's central business district. The city has population of 30,586 as of the 2008 Census projections (U.S. Census Bureau, 2007).

Network Description

Two major roads, Route 30 and Route 1, cross the city and serve as the main entrances/exits of the city, as shown in Figure 5.2. Both are dual four-lane arterial roads. The study area is in the eastern portion of Chicago Heights, covering approximately one eighth of the city. The speed is modeled as 30 to 40 mph for arterial roads and 20 to 25 mph for local roads.
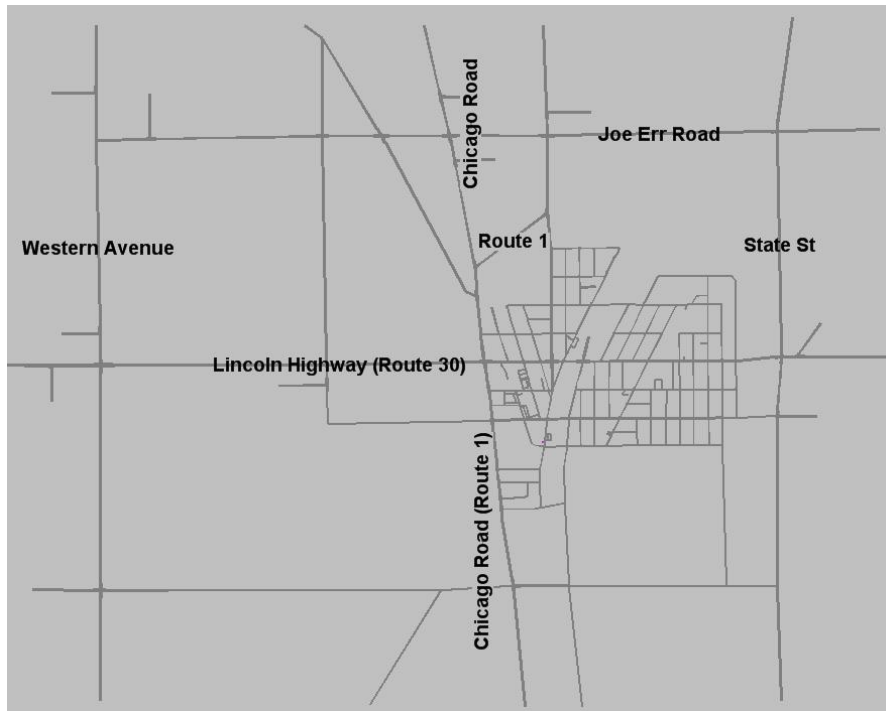
Figure 5.2. Road Network in VISSIM

Six bus lines operate in the study area. One major terminal is located within the area, where five bus lines terminate and the other passes through. Buses are assumed to operate every half hour during the evacuation. As evacuation time by bus is based on waiting time and in-vehicle travel time, the bus schedule is important. In order to obtain fair and reasonable results, we assume that the time of bus lines arriving at the network or departing from the network is evenly distributed through the safe evacuation period. This area does not have a rapid transit system, such as train; however, the methodology can be applied to an area with rapid transit.

The simulation period is from 10:50am to 12:00pm; the first ten minutes is the warm-up period, which fills the empty network. The disaster event occurs at 11:00am, and evacuation starts immediately. Travel time is updated every 150 seconds in VISSIM.

Figure 5.3 also shows the three elementary schools, Jefferson (Facility 2), Lincoln (Facility 3) and Dr Charles E Gavin (Facility 4), which had 317, 180 and 183 enrolled students in the school year 2007/2008, respectively. A daycare center, HGDC childcare center (Facility 1) with an assumed 100 children, also requires relocation. The figure also shows eight potential relocation sites, including parks, churches, and a health center.
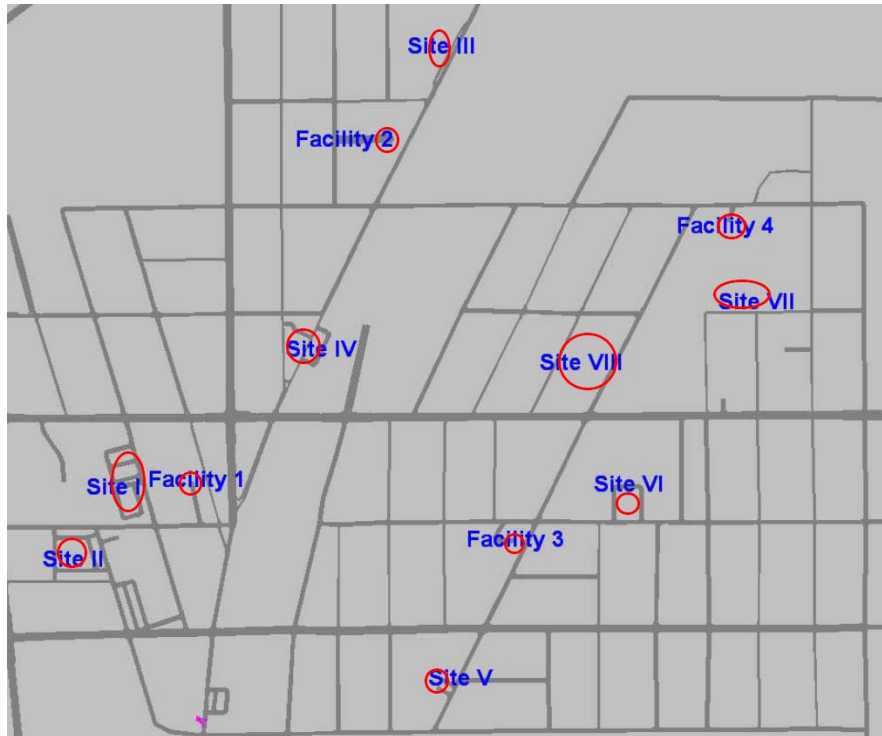
Figure 5.3. Locations of Facilities and Relocation Sites

Evacuation Demand

Travel demand under emergency conditions is composed of background traffic, non-pickup evacuees, and pickup evacuees. Non-pickup evacuees are those in the dangerous area who need to evacuate themselves but do not pick up anyone. Normal travel demand data was provided by the Chicago Metropolitan Agency for Planning. Both non-pickup and pickup evacuation demand are estimated here.

It is reasonable to assume that everyone within the impacted area are evacuees. Since people need to prepare to evacuate, we assume non-pickup evacuees depart within 10 minutes after the disaster occurs. VISSIM assumes a Poisson arrival distribution within a time interval (PTV AG, 2005). The number of non-pickup evacuees is estimated based on the number of employees and unemployment status from Census data (U.S. Census Bureau, 2007). Based on the population over 20 years old, the size of the area, 90% of the population being in Chicago Heights on a normal workday, and the average vehicle occupancy of 1.1 - 1.3, we estimated 1350 non-pickup evacuees. Ten internal zones, evenly distributed within the study area, were created to represent origins for non-pickup evacuees. They choose the closest destination.

Pickup evacuees originate from where they are - either outside or inside the affected area - at the moment the disaster strikes. The affected area has a 2 mile radius, thus pickup evacuees are most likely outside the area. We assume 80% are outside the dangerous zone and 20% are inside. For pickup evacuees originating inside the affected area, departure time follows a normal distribution with a mean of 5 minutes (after the disaster occurs) and a standard deviation of 1.25 minutes. Their origins are evenly distributed among internal zones of the network, and destinations are evenly distributed among external zones. For pickup evacuees starting outside the affected area, we examine the time they arrive at the network instead of when they depart from their origins. Arrival time follows a normal distribution with a mean of 20 minutes and a standard deviation of 2.5 minutes. Destination choice follows a uniform distribution. Origins are determined according to the assumption that 80% of pickup evacuees who depart from outside the affected area are from the Chicago central business district direction.

The total number of pickup evacuees is determined by the number of dependents. In this sample application, 780 dependents need to be picked up; as one parent is assumed to be responsible for 1.11 children on average, the number of parents is 702. In reality, the average number of students that one parent is responsible for is probably higher; in this sample application, 1.11, a relatively low number, is chosen in order to reflect worse cases. The time required for pickup evacuees to find and pick up their dependents, μ, is initially assumed to follow a normal distribution with a mean of 90 seconds and a standard deviation of 20 seconds.

Scenario Analysis

Under emergency conditions, mode shifts may occur to increase the possibility of successful evacuation. Two scenarios were investigated regarding mode shifts: 1) no mode shift and 2) mode shift from car to bus. Mode shift from bus to car is not included because it is subject to car availability and could not take place in reality. Five to ten iterations were required to reach convergence for all cases mentioned in this paper.

Scenario 1 – No Mode Shift between Car and Bus

First, we assume that evacuees use their normal modes for evacuation, so there is no mode shift. Three cases of safe evacuation time thresholds, 30, 45 and 60 minutes, are tested. Table 5.2 shows the number of successful pickup evacuees, S^P, before and after implementing the

relocation strategy, and optimal relocation sites; the values in parentheses represent S^P for each facility, and the values outside parentheses represent the total S^P for all four facilities.

Average speed over groups of traffic (i.e., pickup evacuees, non-pickup evacuees, background traffic, and overall network) was selected as the measure of effectiveness to reflect the performance of the relocation strategy; percentage increase in average speed from the no-relocation case represents network performance improvements. Pickup evacuees, non-pickup evacuees and background traffic are evaluated separately and then performance evaluation is conducted for the overall network, as shown in Figure 5.4.

Table 5.2. Number of Successful Pickup Evacuees before and after Relocation for Scenarios 1 and 2

	T_0 (min)		Number of Successful Pickup Evacuees (S^P)			Optimal relocation sites
			No relocation	With relocation	Improvements	
No mode shift	30	Car:	99 (10, 30, 26, 33)	102 (11, 32, 25, 34)	3 (1, 2, -1, 1)	[V[a], VIII, -[b], 2]
		Bus:	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	
		Total:	99 (10, 30, 26, 33)	102 (11, 32, 25, 34)	3 (1, 2, -1, 1)	
	45	Car:	429 (58, 142, 108, 121)	470 (58, 180, 109, 123)	41 (0, 38, 1, 2)	[I, VIII, VI, 2]
		Bus:	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	
		Total:	429 (58, 142, 108, 121)	470 (58, 180, 109, 123)	41 (0, 38, 1, 2)	
	60	Car:	542 (73, 195, 137, 137)	585 (73, 232, 137, 143)	43 (0, 37, 0, 6)	[I, VIII, VI, VIII]
		Bus:	4 (2, 0, 2, 0)	55 (2, 27, 11, 15)	51 (0, 27, 9, 15)	
		Total:	546 (75, 195, 139, 137)	640 (75, 259, 148, 158)	94 (0, 64, 9, 21)	
Mode shift	60	Car:	467 (58, 190, 106, 113)	467 (58, 190, 106, 113)	0 (0, 0, 0, 0)	[II, VIII, II, VII]
		Bus:	3 (1, 2, 0, 0)	30(1, 14, 4, 11)	27 (0, 12, 4, 11)	
		Artificial Shift:	0 (0,0,0,0)	26 (4,8,12,2)	26 (4,8,12,2)	
		Total:	470 (59, 192, 106, 113)	523(63,212,122,126)	53 (4,20,16, 13)	

[a] Arabic numbers 1-4 indicate facilities; I-VIII indicate relocation sites.

[b] Dash represents that the optimal relocation site for a facility is its current location, i.e., no relocation is needed for this facility.
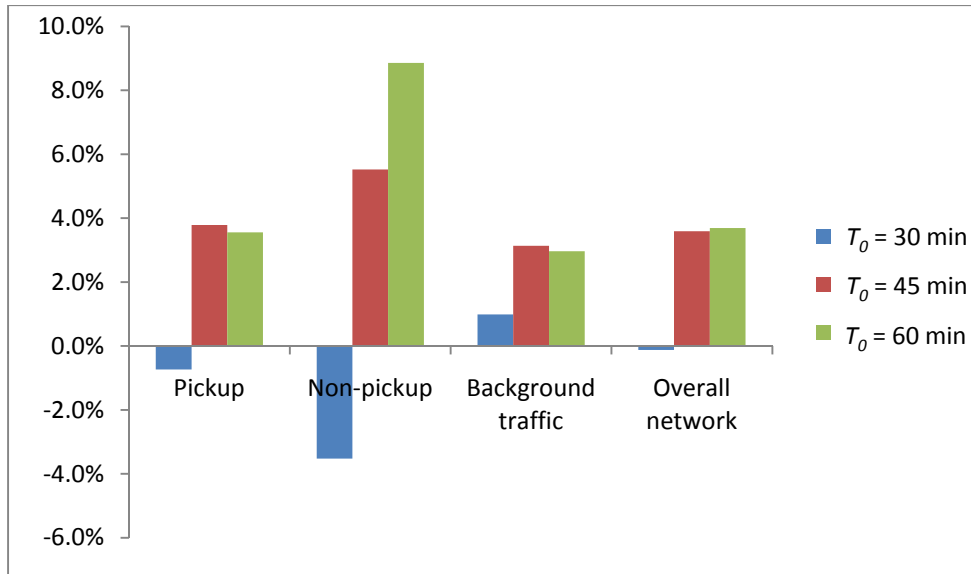
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Figure 5.4. Improvements of Average Speed after Relocation

From Table 5.2 and Figure 5.4, it was found that the safe evacuation time threshold, T_0, plays a crucial role in the relocation strategy. In this sample application, when T_0 is 30 minutes, no significant increases of S^P or clear improvements in performance of any group of traffic were achieved. For the cases of $T_0 = 45$ and 60 minutes, S^P increased by 41 and 94 families, respectively; network performance clearly improved (Figure 5.4), which implied that implementing the relocation strategy not only benefits those involved with pickup issues, but also the other vehicles in the network. Thus, the relocation strategy is only effective when the safe evacuation time threshold is adequate. Table 5.2 showed that Facility 2 achieved the greatest benefit from the relocation strategy, and it contributed to more than 90% of total improvements. No significant improvements were found for other facilities. As optimal relocation sites were different over T_0, this finding is quite useful for the final recommendations.

Evacuation by bus was less efficient than car, from the pickup evacuee perspective. In this sample application, after applying the logit mode choice model, around 120 out of 702 travelers chose bus. The results showed that when T_0 is 30 or 45 minutes, no successful evacuation by bus was achieved. This result could differ if bus service were streamlined for express-stop service only or offered more frequently during emergency conditions. As buses require more travel time, they will not be an efficient way to get out of the dangerous zones when safe evacuation time is tight (at least with the currently modeled service). More frequent service might be less useful than skip-stop service. For the scenario of $T_0 = 60$ minutes, after

relocation, 55 pickup evacuees can successfully evacuate by bus with their dependents (approximately 50% of the total pickup trips by bus), but only 4 can do so before relocation. So, relocation could significantly benefit those who rely on public transit to evacuate when safe evacuation time is adequate.

Scenario 2 – Mode Shift from Car to Bus

In this scenario, Equation (7) replaces Equation (1-1) of the optimization model to include mode shift from car to bus. In Equation (7), the number of successful pickup evacuees (S_{ijkl}) is composed of three parts: 1) successful evacuees by car; 2) successful evacuees by bus who shift their modes from car; and 3) successful evacuees by bus without mode shift. Y_{ijkl}^a is a binary integer variable that indicates whether mode shifts from car to bus occur or not. The assumption is that pickup evacuees change from car to bus if they cannot leave the dangerous zone before a certain time threshold by private car, but they can do so by bus. Y_{ijkl}^a can be calculated from A_{ijkl}^m.

$$S_{ijkl} = \sum_k \sum_{a=0}^{A_{ijkl}^c} q_{ijk}^{a,c} x_{kl}(1 - Y_{ijkl}^a) + \sum_k \sum_{a=0}^{A_{ijkl}^b} q_{ijk}^{a,c} x_{kl} Y_{ijkl}^a + \sum_k \sum_{a=0}^{A_{ijkl}^b} q_{ijk}^{a,b} x_{kl} \qquad \forall i,j,l \qquad (7)$$

Considering that it usually takes much more time to travel by bus than car, we doubled bus frequency to increase the possibility of mode shift from car to bus. However, after running the three time thresholds, no mode shift from car to bus was found.

Artificial shifts to bus were then tested for the case of $T_0 = 60$ minutes: 20% of drivers (132 families) were assumed to have no access to their automobiles because of the emergency and thus needed to shift to transit. The results, shown in Table 5.2, indicated that 26 families who shift can successfully evacuate by bus after relocation, while none of them are able to do so without relocation, which, again, supported the findings that relocating children benefits transit users. Different optimal sites were found for facilities 1, 3 and 4 when considering artificial shifts to transit, which implied that optimal sites are sensitive to mode choice.

Rapid transit may be more frequent and travel faster than buses, meanwhile it is not affected by the road traffic because it occupies special infrastructure. It may be competitive with cars for evacuation, thus mode shifts from car or bus to rapid transit can be expected if rapid transit is included.

Sensitivity Analysis

Sensitivity to Arrival Time by Car

The relocation strategy is sensitive to many factors, such as arrival time of pickup evacuees by car. The previous tests assumed that the arrival time by car follows a normal distribution with a mean of 20 minutes and a standard deviation (σ) of 2.5 minutes. Here we examine the scenario that the standard deviation is 10 minutes. These two standard deviations were selected to represent two situations; 2.5 minutes represents that parents arrive at the network in a short time period; 10 minutes represents that their arrival times are spread over a longer time period. These two situations change road traffic patterns, and they may also affect the strategy's performance. We therefore selected this parameter to use as a sensitivity test. Table 5.3 compares the results for the two car arrival time distributions.

Table 5.3. Comparison of the Optimal Relocation Sites and Number of Successful Pickup Evacuees for Two Auto Arrival Time Distributions

T_0 (min)	Improvements of Number of Successful Pickup Evacuees			Optimal relocation sites	
		$\sigma = 2.5$min	$\sigma = 10$min	$\sigma = 2.5$min	$\sigma = 10$min
30	Car:	3 (1, 2, -1, 1)	27 (8, 13, 5, 1)	[V, VIII, -, 2]	[II, VIII, -, 2]
	Bus:	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)		
	Total:	3 (1, 2, -1, 1)	27 (8, 13, 5, 1)		
45	Car:	41 (0, 38, 1, 2)	17 (8, 11, 0, -2)	[I, VIII, VI, 2]	[II, VIII, -, VII]
	Bus:	0 (0, 0, 0, 0)	3 (1, 1, 1, 0)		
	Total:	41 (0, 38, 1, 2)	20 (9, 12, 1, -2)		
60	Car:	43 (0, 37, 0, 6)	38 (16, 22, -1, 1)	[I, VIII, VI, VIII]	[II, VIII, VI, VIII]
	Bus:	51 (0, 27, 9, 15)	47 (0, 29, 11, 7)		
	Total:	94 (0, 64, 9, 21)	85 (16, 51, 10, 8)		

For the standard deviation of 10 minutes, dependents in Facility 1 benefited from relocation to Site II in terms of increases of S^P, (i.e., 8, 9 and 16 families for $T_0 = 30$, 45 and 60 minutes, respectively), compared with no increase of S^P for the case of standard deviation is 2.5 minutes. Thus, car arrival time distribution affects optimal relocation sites in certain cases. Facility 2 remained relocated to Site VIII for both standard deviations and all time thresholds. For $T_0 = 30$ and 60 minutes, Facilities 3 and 4 (for the case of $\sigma = 10$ min) were relocated to the same sites as $\sigma = 2.5$ min. Comparing network performance improvements for the two arrival time distributions, higher standard deviation caused less network improvement with relocation

for most of the cases, because higher standard deviation spreads the demand and causes less deterioration of network traffic. As a result, network performance improvements through relocation are not as apparent as in the case with lower standard deviation. Site VIII has more entrances/exits than other sites or facilities; and it was selected as optimum more frequently than the other facilities. In this regard, physical configuration of alternative sites and their surrounding road network affects optimal sites, and advantages of multiple entrances/exits show up under emergency conditions.

Sensitivity to Bus Arrival Time

In the tests above, the time when buses arrive at the network was pre-specified for each line, (i.e., the first buses arrive 5-15 minutes after the evacuation order is issued and the next buses arrive 30 minutes later), considered as the baseline bus arrival time. In order to investigate sensitivity of the proposed strategy to bus arrival time, two more scenarios were tested with bus arrival time 5 and 10 minutes ahead of the baseline, for $T_0 = 60$ minutes considering mode shifts from car to bus; the results are shown in Table 5.4. The baseline bus arrival time or 5 minutes ahead of the baseline performed better than 10 minutes ahead, as S^P by bus is higher after relocation (44 and 39 families rather than 28 families). In this regard, bus arrival time (or bus schedule) influences the performance of the relocation strategy and should gain more attention when applying the strategy to reality.

Table 5.4. Number of Successful Pickup Evacuees for Different Bus Arrival Times, Considering Mode Shifts from Car to Bus ($T_0 = 60$ min)

		Number of Successful Pickup Evacuees			Optimal relocation sites
		No relocation	With relocation	Improvements	
baseline	Car:	538 (71, 191, 137, 139)	590 (71, 236, 137, 146)	52 (0, 45, 0, 7)	[I, VIII, II, VII]
	Bus:	4 (2, 2, 0, 0)	44 (3, 22, 8, 11)	40 (1, 20, 8, 11)	
	Shift:	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	
	Total:	542 (73, 193, 137, 139)	634 (74, 258, 145, 157)	92 (0, 45, 0, 7)	
5min ahead of baseline	Car:	528 (73, 176, 138, 141)	597 (73, 236, 138, 150)	69 (0, 60, 0, 9)	[-, VIII, II, VIII]
	Bus:	39 (7, 25, 0, 7)	39 (7, 25, 0, 7)	0 (0, 0, 0, 0)	
	Shift:	9 (0, 7, 0, 2)	0 (0, 0, 0, 0)	-9 (0, -7, 0, -2)	
	Total:	576 (80, 208, 138, 150)	636 (80, 261, 138, 157)	60 (0, 53, 0, 7)	
10min ahead of baseline	Car:	587 (71, 232, 136, 148)	593 (72, 237, 136, 148)	6 (1, 5, 0, 0)	[II, VIII, II, VII]
	Bus:	1 (0, 1, 0, 0)	28 (11, 0, 17,0)	27 (11, -1, 17, 0)	
	Shift:	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	0 (0, 0, 0, 0)	
	Total:	588 (71, 233, 136, 148)	621 (83, 237, 153, 148)	33 (12, 4, 17, 0)	

Sensitivity to the number of non-pickup evacuees was also examined, in conjunction with the distribution of pickup time at the relocation sites. In this second case, the number of non-pickup evacuees are assumed to be 1650 vehicles and pick-up time is assumed to follow a normal distribution with a mean of 180 seconds and a standard deviation of 40 seconds, it was found that for $T_0 = 30$ minutes, S^P is 76 and 99 families before and after relocation, respectively, for $T_0 = 45$ minutes, the values are 284 and 327 families, and for $T_0 = 60$ minutes the values are 477 and 571 families. Compared with the first assumptions of evacuation demand, the values of S^P reduced; however, increases of S^P over the no relocation case were still significant, which implied the benefits of the relocation strategy in the situations of greater evacuation demand and longer pick-up time.

Optimal Relocation Sites

The optimal sets of relocation sites were spatially and functionally diverse across scenarios and cases. This is not feasible for schools or other facilities with dependents to implement in practice. Additionally, by running these scenarios, the determined "optimal" set may not be significantly better than the second or third optimal set found during the iteration process, and sometimes the differences between them were quite slight. It was also found that in some cases multiple optima exist because several sets provide the same results. It is not necessary to hit the optima to realize network performance improvements through relocation. Therefore, for the purpose of practical application, we present the recommended optimal set(s), [I, VIII, VI, VII] for this sample application based on the results of the tests and other subjective reasons. Site VIII was selected for Facility 2 since it was optimal for all cases; Sites I, VI, VII were selected for Facilities 1, 3 and 4, respectively, as they were optimal for most cases, and they were closer to the current facility locations, facilitating the transfer of students to the new site.

Conclusions

This paper presented a linear integer program to determine optimal sites where schools and other care facilities can move their dependents for pickup in a no-notice evacuation. The evacuation time period is discretized into several time intervals to reflect the fact that road traffic is dynamic in a no-notice evacuation.

The optimization model used anticipated travel time generated from the simulation model, thus the two models interact with each other. In order to deal with the interaction, iteration between the two models was performed and a procedure to accomplish the iteration was proposed. The whole methodology was applied to a sample network based on Chicago Heights, Illinois. The sample application involved four facilities with 780 dependents, three safe time thresholds, (i.e., 30, 45 and 60 minutes) and two transport modes (i.e. autos and buses).

The safe evacuation time threshold was quite important for the relocation strategy. When the safe evacuation threshold is tight, relocation is not effective and inappropriate; however, with adequate time, relocation benefits both those picking up dependents and the other vehicles in the network. Even though evacuation by bus is less efficient than car (from the pickup evacuee perspective), with an adequate time threshold, relocation could significantly benefit those who rely on public transit to evacuate. Results also suggested site physical configuration affected the optimal sites, and multiple entrances/exits are advantageous under emergency conditions.

The contributions of this research are the development of an optimization-simulation model to determine optimal sites to move facilities' dependents to under no-notice evacuation conditions. The results of the model can be incorporated into evacuation plans for a city and to assist emergency managers directing no-notice evacuation more effectively. Pre-disaster planning and agreements among facilities and caregivers about dependent relocation could improve network performance.

Future directions

As previously mentioned, the current optimization model is deterministic. To handle the randomness of both the micro-simulation and mode choice models, stochastic optimization methods could be introduced to incorporate probabilistic elements (different combinations of optimal relocation sites may be achieved for different runs because of random seeds). In the future, an algorithm determining optimal bus routes and schedules could be integrated with the presented model. Additionally, a full case study with more facilities and more transportation modes, such as rail, tram, or bus rapid transit, will be conducted in the future.

Chapter 6 Summary and Conclusions

This dissertation is one of the first to address household gathering behavior in no-notice events based on stated behavior. This study is largely based on 315 interviews conducted in the Chicago metropolitan area, in which participants were posed with scenarios of no-notice events requiring evacuation of different radii. Reported anticipated behavior was analyzed for household pick-up and gathering behavior and used to develop models to represent the behavior. This dissertation provides a method to integrate the household behavior models with network simulation modeling to examine the effects of household behaviors on network clearance time. Experimental applications are tested on the network of the Chicago metropolitan region for two hypothetical incidents: (a) a small-area evacuation (no-notice workplace evacuation without home evacuation), and (b) a large-area evacuation (no-notice workplace evacuation with home evacuation). This dissertation also presents an optimization model to determine optimal relocation sites for facilities (e.g. schools) caring for dependents (e.g. children) that may need to be picked up during the evacuation. The relocation sites can facilitate the gathering process to the benefit of both those with and without pick-ups to make.

Based on the interviews, logistic regression models were built to predict the probability that parents retrieve children from school in normal and emergency situations. Gender, car availability, and travel distance (between parents and children) were found to be the main influencing factors to determining child-chauffeuring travel behavior, where gender difference appeared to be the most prominent. It was found that women are more responsible for picking up children from school than men, and both women and men are more likely to pick up children under emergency conditions than they are in normal situations. Effects of car availability on child-chauffeuring behavior depend on the emergency's geographic scale: for a minor incident leading to a small-scale evacuation, effects of car availability are not significant, while for a major disaster requiring a large-scale evacuation, effects of car availability become significant. Distance between a parent and a child is another factor significantly affecting child-chauffeuring behavior in normal and emergency situations. On a normal weekday, the farther parents are from children, the less they are likely to pick them up; this phenomenon still remains for mothers under emergency conditions, but no longer exists for fathers. In other words, the likelihood of a

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father picking up a child in an emergency is not affected by distance. The study also explored spouse-gathering behavior and mode choice patterns under emergency conditions. The results showed that commute modes and car availability are the most influencing factors for minor and major incidents. Gender did not significantly affect spouse-gathering; that is, men and women are almost equally likely to gather spouse in case of emergency.

This dissertation presented a model framework to integrate household behavior and traffic assignment modeling. The framework follows the traditional four step planning structure to: 1) estimate household gathering chains in an evacuation using a discrete choice (Logit) model and sequence the chains following the principle of "nearest first", 2) assign directions of destinations ensuring the least travel time to safe zones from the last stop within the hot zones, 3) apply decision tree based mode choice models to determine the mode used for evacuation, and 4) use a dynamic assignment method to assign time-varying demand to the network. The whole framework was tested in the Chicago metropolitan region for two hypothetical incidents, one causing a 5-mile evacuation radius and the other a 25-mile radius evacuation. The results showed that considering household gathering behavior will reduce proportions of evacuees who reach safe zones by a certain time period, while not necessarily deteriorating overall network traffic performance. Overall network clearance times were increased due to the intermediate trips but these trips reduced congestion on some links important for evacuation out of a hot zone. Traffic patterns were different when gathering behavior was taken into account, which has implications for the success and public perception (post event) of evacuation management strategies. If the behavior is not accounted for, strategies may impede the gathering phenomenon, causing additional delays for those households and potentially the entire evacuating population.

To facilitate the pick-up of dependents in no-notice evacuations, facilities (e.g. schools) could move the dependents to nearby, but more accessible, locations. This dissertation presented a linear integer program to determine optimal sites. The optimization model uses estimated travel time obtained from a micro-simulation model and a procedure was presented to iterate between the two models. The methodology was applied to a sample network based on Chicago Heights, Illinois. The sample application involved four facilities with 780 dependents and three safe time thresholds, (i.e., 30, 45 and 60 minutes). The sample application tested two scenarios: no mode shift and mode shift from car to bus, and introduced average speed and the number of successful

evacuations of dependents to evaluate performance of a relocation strategy. The safe evacuation time threshold was quite important for the relocation strategy; when it is adequate, relocating facilities benefits both those picking up dependents and the other vehicles in the network.

This dissertation contributes to the fields of evacuation modeling and transportation engineering, in general. This study investigated child pick-up, spouse gathering, and home gathering behavior during hypothetical incidents, and identified characteristics associated with household decision makers that influence this behavior. The study also presented a model to integrate the behavior with traffic assignment simulation modeling; the combined model could be used to identify potential spatial and temporal bottlenecks and estimate network clearance time. Finally, this work explored a strategy to facilitate household pick up chains by relocating facility dependents to more accessible site. The study can support any city's evacuation plan development.

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