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An Integrated Agent-Based Microsimulation Model for Hurricane Evacuation in New Orleans

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AN INTEGRATED AGENT-BASED MICROSIMULATION MODEL FOR HURRICANE EVACUATION IN NEW ORLEANS

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Abstract

Mass evacuation of urban areas due to hurricanes is a critical problem that requires extensive basic and applied research. Knowing the accurate evacuation time needed for the entire region in advance such that the evacuation order can be issued on a timely basis is crucial for the officials. Microsimulation modeling, which focuses on the characteristics of individual motorists and travel behavior, has been used widely in traffic simulation as it can lead to the most accurate result.

However, because detailed driver response modeling and path processing must be incorporated, vehicle-based microscopic models have always been used only to simulate small to medium sized urban areas. Few studies have attempted to address problems associated with mass evacuations using vehicle-based microsimulation at a regional scale. This study develops an integrated two-level approach by separating the entire road network of the study area into two components, highways (i.e., interstate highways and causeways) and local roads. A vehicle-based microsimulation model was used to simulate the highway part of the road traffic, whereas the local part of the road traffic simulation utilized an agent-based model. The integrated microsimulation model was used to simulate hurricane evacuation in New Orleans. Validation results confirm that the proposed model performs well in terms of high model accuracy (i.e., close agreement between the real and simulated traffic patterns) and short model running time.

Sufficient evacuation time is a premise to protect people's life safety when an area is threatened by a deadly disaster. To decrease the network clearance time, this study also examined the effectiveness of three evacuation strategies for disaster evacuation, including a) simultaneous evacuation strategy, b) staged evacuation strategy based on spatial vulnerabilities,

and c) staged evacuation strategy based on social vulnerabilities. The simulation results showed that both staged evacuation strategies can decrease the network clearance time over the simultaneous evacuation strategy. Specifically, the spatial vulnerability-based staged evacuation strategy can decrease the overall network clearance time by about four hours, while the social vulnerability-based staged evacuation strategy can decrease the network clearance time by about 2.5 hours.

Chapter 1 . Introduction

1.1 Problem Statement

Southern Louisiana is one of the most hurricane vulnerable areas. Recently documented trends in the existing records of hurricane suggest that hurricane intensity may be increasing due to global warming (Kossin et al., 2007). The landfall of the severe hurricanes coincides with high storm surge. Storm winds funnel water from the sea into the coastline and shallow areas. Because we can do little to alter the weather, when a severe hurricane comes, the way to protect people in low-lying areas is to evacuate them to a safer area. However, due to the uncertainty of the hurricane track, the less evacuation time needed for the whole population, the later the officials can issue the evacuation order, which can minimize the possibility of issuing an inappropriate order. At the fundamental level, disaster evacuation is simply moving people away from the endangered areas. However, evacuations in the real situation, particularly evacuations on a massive scale, are complex undertakings (Wolshon, 2006).

There were four major evacuations in New Orleans history, 1998 for Hurricane Georges, 2004 for Hurricane Ivan, 2005 for Hurricane Katrina, and 2008 for Hurricane Gustav. The first two evacuation processes were found to be inefficient. Although the evacuations for Hurricane Katrina and Hurricane Gustav was widely viewed as successful, knowing the accurate evacuation time needed in advance and using a more efficient evacuation strategy to save the evacuation time remains the top concern for the officials.

One of the most important factors influencing the outcome of a natural disaster in terms of human loss and property damage is the evacuation time, which includes three components: initial warning time, individual preparation time, and network clearance time. Initial warning time is the time between the first notification of an existing potential hazard or natural disaster and the time when the order to evacuate is issued. The individual's preparation time is the time between the issuance of an order to evacuate and the final decision to leave the dangerous area. The network clearance time is the time required to clear all evacuating vehicles from the roadways. Clearance time begins when the first evacuating vehicle enters the road network and ends when the last evacuating vehicle reaches its destination. This also includes the time spent by evacuees waiting along the road network due to traffic congestion (Jamei, 1984).

The major focus of this study is on network clearance time, which requires the determination of time required to evacuate all the regional residents at a severe hurricane-threatened site. Historically, disaster evacuation planning has been the responsibility of emergency management and law enforcement agencies, but engineers and transportation researchers have become increasingly involved in the last thirty years. One of the areas in which they have become involved is the development of mass evacuation models.

It is important that modeling techniques be explored to estimate the risk in disaster threatened areas by estimating the time it required to clear a residential neighborhood if an evacuation is needed. Due to the different levels of detail in modeling traffic flow in a simulation, the simulation level can be classified into three basic categories: macroscopic, mesoscopic, and microscopic. Macrosimulation is based on aggregate traffic flow. The implicit assumption in this flow-based model is that the flow on a link is static and homogeneous, which is not the case in real situation, hence making the macrosimulation model relatively inaccurate. Mesosimulation traces explicitly the vehicles' movements, and considers aggregate link performances in a dynamic traffic assignment framework, though some scientiests incorporate it into the macrosimulation level (Sahraoui and Jayakrishnan, 2005). Microsimulation, the finest level, traditionally focuses on the characteristics of individual motorist and travel behavior (Hoogendoorn and Bovy, 2001). In most situations, microsimulation is the best choice as it can lead to the most accurate result (Chen, 2006).

However, because detailed driver response modeling and path processing must be incorporated, traditional vehicle-based microscopic models have always been used to simulate small- to medium- sized urban areas.

Few studies have attempted to address problems associated with mass evacuations using microsimulation even though computer technology has advanced greatly. This is because many network algorithms show a nonlinear increase in storage and computational requirements as network sizes increase (Sahraoui and Jayakrishnan, 2005). Another shortcoming of the microsimulation of disaster evacuation is that the trip generation is based on the origin-destination (OD) matrix input, which may deprive the dynamic destination choice of each vehicle and the matrix may also be too complex if too many OD pairs exist. Furthermore, the way to estimate the OD matrices accurately is also a major challenge to the use of dynamic assignment in the microsimulation models. The last drawback of the microsimulation models is that it needs an accurate input road network, meaning that to fit the microsimulation model's requirement, the input traffic network for simulation must include all the details of the roadways. For the whole regional area, this may require a large amount of time for data preparation and model calibration.

For the regional disaster evacuation situation, most of the time required for road network preparation comes from the preparation of complex local road configuration for microsimulation. However, most of the network clearance time is consumed on the interstate highway, and the interstate highway network is relatively easier to be configured in a microsimulation model. As such, to simulate regional traffic evacuation, a reasonable way would be to separate the whole road network of the study area into two parts; that is, highways (i.e., interstate highways and causeways) and local roads, and to use a vehicle-based microsimulation model to simulate the highway part of the traffic and leave the local road traffic simulation to another more suitable model, which will be discussed in section 3.4. This means that a loosely integrated model could be developed to simulate the traffic flow for the whole regional disaster evacuation. The mechanism used to integrate these two models is called output-as-input, which means that the output of the local traffic simulation model (i.e., O-D matrices) would be the input of the interstate highway traffic microsimulation model.

Both models for the local traffic simulation and interstate highway traffic simulation to be used in this research belong to agent-based models as each vehicle is modeled as an agent. With the emergence of agent-based technologies, interests are rapidly growing in modeling the spatial decision-making processes of the individuals who interact in these dynamic spaces and produce object paths (Bennett and Tang, 2006). Agent-based modeling has been used in many disciplines with great success (Deadman, 1999; Ahearn et al., 2001; Gorman et al., 2006), and the vehicle-based microsimulation is one application (Adler and Blue, 2002; Dia, 2002; Chen et al., 2006). For the local-traffic simulation model in the regional evacuation situation, due to the above-mentioned drawbacks of the macro- and vehicle-based micro- simulation models, this project takes advantage of the agent-based modeling framework by creating a census block centroid-based microsimulation model.

In addition, evacuation strategies may play a role in saving network clearance time, so an appropriate evacuation strategy must be emphasized in this study. In spite of its apparent importance, little effort has been devoted by scientists to find more efficient and realistic evacuation strategies. Among these few studies, Chen (2006) concluded that the staged evacuation strategy is better, in terms of overall evacuation time, than the simultaneous evacuation strategy at certain circumstances. However, Chen’s study divided the study area into four paralleled zones for staged evacuation, which were arbitrary. In this study, we propose to partition evacuation zones based on two types of vulnerability: spatial vulnerability and social vulnerability, respectively. The effectiveness of each evacuation strategy is examined by using the integrated agent-based microsimulation model developed in this study.

1.2 Objectives and Hypotheses

1.2.1 Objectives

Specifically, the primary objectives of this study are:

1) To create a two-level regional disaster evacuation model by integrating two agent-based microsimulation models. The first model treats each vehicle as an agent to simulate the highway part of the regional road network, and the second model uses the census block centroid as an agent to simulate the local part of the regional road network.

2) To determine the effectiveness (i.e., overall evacuation time) of several different regional evacuation strategies. Three evacuation strategies were evaluated in this study:

a. simultaneous evacuation strategy: there is no limitation on the initial evacuation time for all residents. Everyone has the same priority, and can start to evacuate at any time desired after the evacuation order is issued;

b. staged evacuation strategy I based on spatial vulnerability: spatial vulnerability is defined as an estimate of the relative effort required to clear the population of an area, so people in different evacuation area have different spatial vulnerability (Cova and Church, 1997). The reasonable way to evacuate the whole area efficiently and smoothly is to let the high spatial vulnerability residents evacuate first, and then issue the second evacuation order to the rest of the low spatial vulnerability residents. The detail of this spatial vulnerability-based staged evacuation strategy is discussed in section 4.4.

c. staged evacuation strategy II based on social vulnerability: Different areas also have different degree of social vulnerability (Cutter et al., 2000). It is assumed that high social-vulnerability areas will require more time to evacuate. This strategy is to make half of the residents who have high social vulnerability to evacuate first, and after a while, issue the evacuation order to the other half of the socially-vulnerable residents. The detail of this evacuation strategy is discussed in section 4.5.

1.2.2 Hypotheses

The hypotheses of this study are 1) the integrated two-level agent-based microsimulation model can model the regional evacuation very well, with a high degree of accuracy. It can decrease the model running time compared with the traditional vehicle-based microsimulation; 2) By applying a staged evacuation strategy based on the evacuation zones partitioned by different spatial vulnerability, the overall evacuation time can be decreased; 3) The staged evacuation based on social vulnerability can also decrease the network clearance time.

1.3 Significance of This Study

1.3.1 Why Use Two Agent-Based Microsimulation Models

Vehicle-based microsimulation is the most accurate simulation model up to date (Chen, 2006). However, due to the computational and input requirements, it is nearly impossible to simulate the whole regional evacuation situation by using vehicle-based microsimulation only (Sahraoui and Jayakrishnan, 2005). So a reasonable solution to simulate the regional evacuation is to integrate two agent-based microsimulation models which are expected to decrease the simulation and calibration time dramatically. This will enable decision-making agencies to examine the simulation results on a more timely basis.

1.3.2 Why Use Different Evacuation Strategies

Even though we already know that the staged evacuation can decrease the overall evacuation time at given scenarios (Chen, 2006), the available evacuation strategies are very limited. It is reasonable to assume that residents with high vulnerability will take more time to evacuate and hence should evacuate before the low-vulnerability residents evacuate. As to the vulnerability, this study evaluates the effects of spatial vulnerability (Cova and Church, 1997) and social vulnerability (Cutter et al., 2000), respectively, on the network clearance time.

1.3.3 Why the Particular Study Area

New Orleans is one of the most vulnerable hurricanes-threaten areas (Cutter et al., 2006). There were about 124,000 vehicles in the evacuation process (Post, Buckley, Schuh & Jernigan, Inc., 2000), and no former study simulated the evacuation of this entire metropolitan area.

In summary, this dissertation contributes to the fields of dynamic spatial modeling, visualization, and disaster and vulnerability sciences. The study is innovative mainly in four aspects: 1) for the proposed census block centroid-based microsimulation model, each agent can dynamically choose its evacuation destination (i.e., highway access); 2) by combining the census block centroid-based microsimulation model with vehicle-based microsimulation model and using social-economic data, we can extend the microsimulation study scope from local to regional, with reasonable simulation running time and accuracy; 3) The evaluation of the two-staged evacuation strategies informs decision-makers of the evacuation clearance time needed for each evacuation strategy; 4) based on the census block centroid-based microsimulation model, a user friendly simulation interface is created which can show dynamically the entire traffic evacuation process and help inform decision-makers and the public.

Chapter 2 . Literature Review

Most of the studies concerning the natural disaster evacuation planning are generally classified into two broad categories: 1) human response studies, and 2) engineering studies (Jamei, 1984). This study focuses on both aspects: first, the evacuation strategies in this study try to analyze and utilize the human evacuation response rate to relieve the traffic congestion. Second, a computer microsimulation model to simulate the traffic flow for regional disaster evacuation would be developed.

Meanwhile, different evacuation strategies based on different kinds of vulnerability is another major concern of this study. This review focuses on four topics: regional evacuation modelling, microsimulation of evacuation, agent-based modelling, and staged evacuation. Based on this literature review, the last section of this chapter summarizes the overall characteristics of regional evacuation modelling and agent-based microsimulation models, and further points out the significance of this study.

2.1 Regional Evacuation Modeling

2.1.1 Introduction

Humans live in an environment full of both man-made and natural hazards, such as nuclear reactor failures, chemical releases, dam-failure related flooding, hurricane, volcanic eruptions, tsunami and earthquakes (Southworth, 1991). In addition to the recent event for the San Diego, California, forest fire evacuation in 2007, numerous regional evacuations occur every year in response to various kinds of man-made or natural disasters, such as chemical spills, flash flooding, and tsunami, etc. To protect the residents from these disasters, regional evacuation plans are needed. Even though the characters of each disaster may vary dramatically and should be considered while enact the evacuation plan, but the premise of evacuating endangered residents is the universal consensus and only means of ensuring a resident's safety. However, how to make the evacuation process progress as planned poses a significant challenge because of its complexity. To develop evacuation plans but also the process by which we apply such plans during the course of any emergency evacuation, prior knowledge of how people will respond to both publicly sanctioned and spontaneously generated forms of information (Southworth, 1991).

With the advance of computer technology, the interests of quantitative traffic modeling to obtain the evacuation clear time needed have drawn more and more attention. Recording from the evacuation order issued, clear time means the time to evacuate all the endangered residents reaching a safe area must be known. However, this process may be not smooth. It may be accompanied by with serious traffic congestion. In some instances such delay could lead to loss of life (Southworth, 1991).

2.1.2 Evacuation Modeling

To develop a simulation model for mass population, a set of accurate information is needed beforehand, such as the road network (including both local and highway parts), the spatial distribution of population and their social-economic data, vehicle utilization during an emergency of the type under consideration, the people's response rate (i.e. when to make the decision to evacuate) to the emergency affected by many personal and environmental factors, available evacuation routes, and destination selection behavior. By adjusting a selection of alternative evacuation routes, destination, evacuation sequence and evacuation response rates, scientists can evaluate the effectiveness of the different evacuation strategies. This process of generating regional evacuation models, thus simulating its expected network clearance (evacuation) times requires a five-step process. These are 1) traffic generation sub-model, 2) traffic departure time (often termed as traffic loading rate or traffic mobilization) sub-model, 3) destination selection sub-model, 4) traffic route selection (often termed as traffic route assignment) sub-model, and 5) user specified plan set-up, analysis and revision procedure (Southworth, 1991). The following is a brief description of each sub-model.

2.1.2.1 Traffic Generation Sub-model

This traffic generation sub-model is primarily to load the number of vehicles onto the road network at each area. While this number varies at each time period of day, Glickman (1986) points out the considerable discrepancies between daytime and nighttime population distributions at the beginning time of evacuation. The census information on the number of residents by area can be used as the population distribution at night, but daytime evacuations require considerably more data collection effort, which makes it considerably difficult to obtain such information. So to estimate the daytime population distribution, location-specific populations are often classified in several groups as: at home populations, at work populations, at school populations, and special facility populations (e.g. hospitals, colleges, hotels, recreational centers, etc.) However, for disaster evacuation, this day time/night time difference should be considered only in the situation of abrupt disaster. For hurricane evacuation, since most of the residents already have expected evacuation, they would begin to evacuate from home with all their family members. This means that we can use the number of residents in small census areas as the population distribution for the traffic generation model in this hurricane evacuation study.

Another issue about the traffic generation is how to translate the number of evacuees into the number of evacuation vehicles, which is the simulation unit in the simulation model. However, there is few published literatures on the derivation of vehicle utilization rates during emergency evacuations, so we are currently left to rely on one of the following three approaches, none of which are entirely satisfactory (Southworth, 1991): 1) post-evacuation survey results; 2) results from a questionnaire (containing questions such as what they would do in certain hypothetical circumstances); 3) estimation by using information such as household size and commute vehicle occupancies.

Among these few studies, Baker (1979) examined the possible translation rate by using post-evacuation surveys. He reported that the vehicle utilization rate was 75% under different emergency situations and geographic location. Perry and Greene (1983) noted that a post-evacuation survey associated with the Mount St. Helens eruptions revealed that vehicle utilization rate was only 52%. Based primarily on estimates derived from evacuation intent surveys, Rogers et al. (1990) tried to estimate the number of vehicles participating in the evacuation by using population information. He reported that the result was in the range of 2.0 to 2.5 persons per vehicle in the post-evacuation studies.

In this study, this translation rate is not required to estimate the numbers of evacuation vehicles. This is because the number of evacuation vehicles can be estimated from traffic count data of former evacuation cases (e.g., Hurricane Katrina). The number of vehicles for each census block and thus the overall vehicles can also be obtained from social-economic data. The vehicle participation rate is assumed to be the same for all the census block groups, so the estimated number of vehicles can be acquired for every census block group in the disaster endangered area.

2.1.2.2 Traffic Departure Time

The traffic loading rate sub-model contains a critical assumption, which affects all subsequent time analysis for the hurricane evacuation event, about the time distribution of the percent of evacuees leaving vulnerable areas (Jamei, 1984). In practice, it can be expected that some residents will begin to evacuate even before the issue of evacuation order (fewer than 15% to 20% of evacuees usually depart prior to evacuation notices being issued by public safety officials) (Radwan et al. 1985). However, others may delay their decision based on the official instruction. A portion of residents will not evacuate at all, and can be considered to be a residual at risk population.

There are four major methods for estimating the traffic loading curve or evacuee mobilization time curve: 1) those based upon past empirical evidence (i.e. post-evacuation surveys); 2) those based upon surveys of the possible evacuees beforehand; 3) those based on the expert and planner estimation and judgment of human response under emergency; 4) those based on the simulation of the diffusion of emergency warning system messages and the subsequent spread of information within the endangered community (Southworth, 1991).

The first approach is widely used. The U.S. Army Corps of Engineers (USACE) proposed three different response curves (USACE, 2000), for slow, medium, and rapid responses respectively, based on behavioral analysis of past storms (Figure 2.1). This curve shows the cumulative response distributions that starts at a low rate at the beginning and as time progresses the rate increases until it reaches its maximum threshold around halfway through the total loading period. The cumulative volume plotted over time takes an 'S-shape' curve for any type of response curves (Jamei, 1984). One of the major goals of the loading curve is to help emergency management officials schedule issuance of evacuation notices. That is, the loading curve indicates the latest time that decision-makers must post the evacuation notice before all the residents can be evacuated safely.

The most popular model to calculate the loading rate has been the logistic model, and Radwan et al. (1985) and Hobeika and Changkun (1998) used it to model the loading time of trips onto the highway network during an evacuation from natural disaster in their MASSVAC model:

$$P(t)=1/\{1+exp[-a(t-b)]\}$$

where $P(t)$ is the cumulative percentage of the total trips generated at time t. Parameter a,

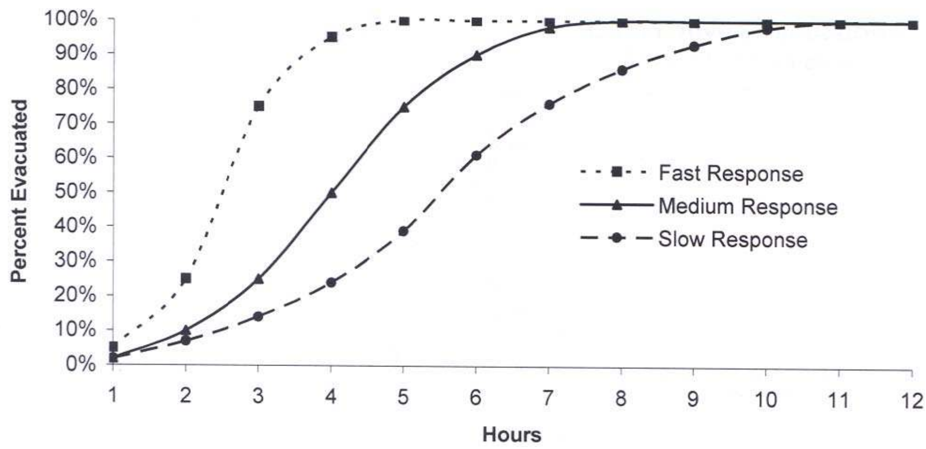


Figure 2.1. Three different response curves (Source: Jamei, 1984)

which controls the steepness of the curve, is the slope of the 'S-shape' curve. A higher *a* value would make the curve flat toward the end and steeper in the middle. Using the results from previous studies, values of 0.04, 0.022, and 0.01 are used for steep, flat, and lazy curves respectively (Jamei, B. 1984). *b* is the half loading time, the time at which half of the vehicles in the system have been loaded onto the road network. The logic behind selection of the *b* value is the time limit which is available for evacuation purposes (Jamei, 1984). However, this model does not take into account the fact that the traffic volume varies at each time period of day.

Based on the evacuee departure times from post-Hurricane Floyd telephone survey, the Southeast United States Hurricane Evacuation Traffic Study compiled the data into cumulative response curves for some regions in the affected area (FHWA, 2005). The loading rate curve should be a smooth 'S-shape' by using the logistic model for these different regions. However, the result shows that even though it is generally 'S-shape', the curves are different from region to region (Figure 2.2), they are irregular rather than "smooth", and departures extend over days rather than hours. Thus, it appears as if departure behavior is correlated to not only the time since an evacuation order was issued (Fu, 2004). Fu identified the factors affecting evacuation departure behavior and incorporated them into individual storm scenarios. Two datasets were used in Fu's (2004) study. The post-hurricane Floyd survey in South Carolina was used to estimate the model. The dataset for post Hurricane Andrew survey in southeastern Louisiana was used to test the model. Part of the Floyd dataset was also set aside for model testing. A sequential logit model has been developed to estimate dynamic travel demand for hurricane evacuation. It is a disaggregate model that predicts when households will evacuate in the face of an oncoming hurricane by assuming that the decision to evacuate has already been made. The model is sensitive to the characteristics of the storm, the characteristics of the household,

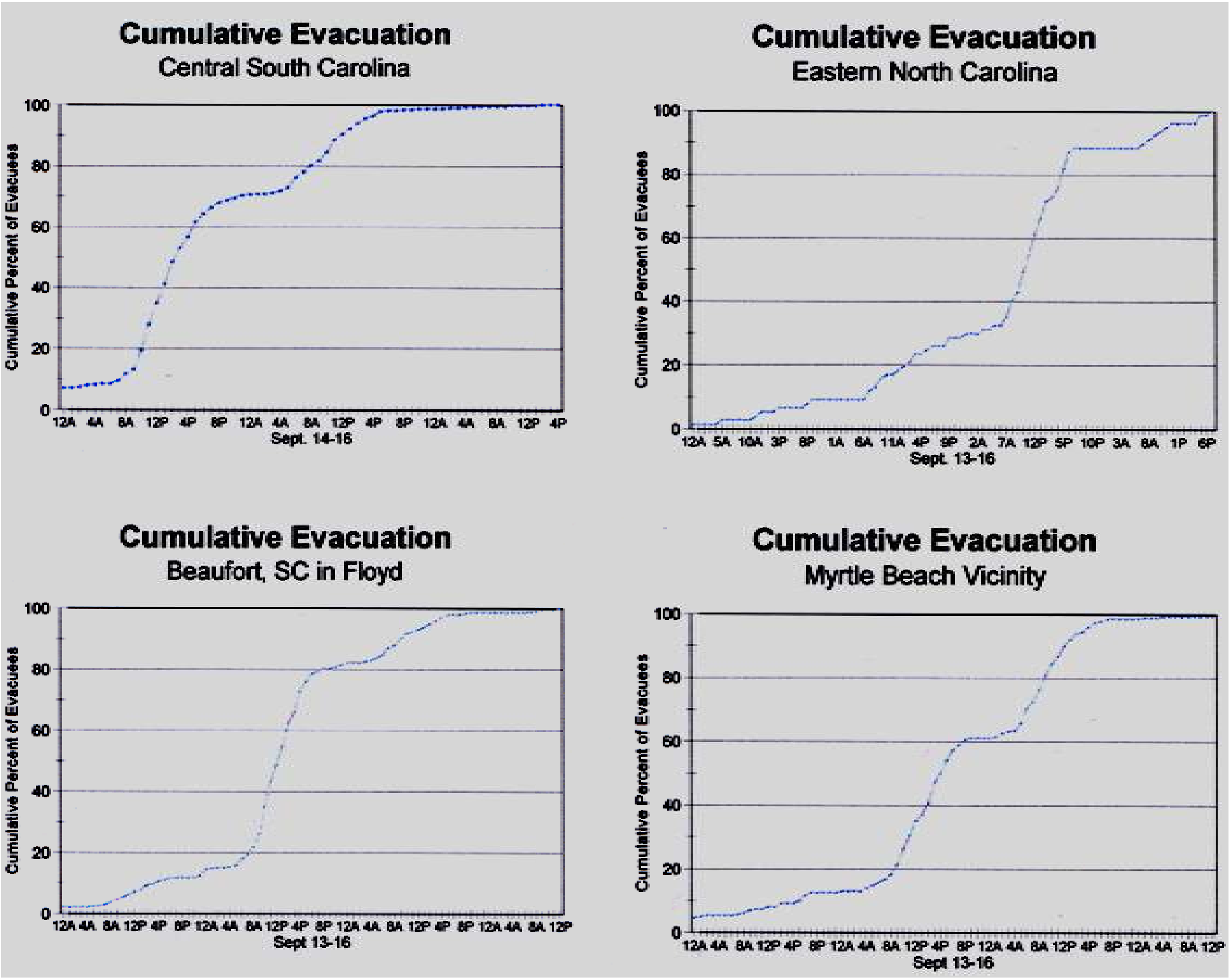


Figure 2.2. Hurricane Floyd evacuation curves (Source: Fu, 2004)

and the evacuation policy adopted by the authorities. The unit in this demand model is one household, and the model concentrates entirely on when these households to evacuate.

Even though Fu's (2004) study noticed that the individual response is affected by many factors, the problem of the response curve affected by some factors for the evacuees as a whole is still not resolved.

2.1.2.3 Destination Selection Sub-Model

When the individual evacuates, his/her destination is usually not selected randomly. The choice is normally made by one of the following criteria (Southworth, 1991):

1) "Evacuees will head toward the nearest destination in terms of distance and expected travel time to exit the disaster threatened area;

2) The destination selection displays some degree of dispersion. The factors that can affect this dispersion include location of friends and relatives as well as shelters, and the speed of the hazard onset;

3) If there exist some pre-specified destinations, some evacuees will head toward these places;

4) Evacuees will take real-time traffic condition into consideration at the time they attempt to leave the area."

The first method often happens in a rural or small urban system evacuation. If the hazard (e.g. hurricane) is not approaching rapidly toward the regional area, many evacuees that have relatives or friends living in nearby safe areas, and others that have simply better hopes of overnight shelter elsewhere (e.g. hotels), may disperse into these kind of destinations (Southworth, 1991). Method two is often used by the modeler to assess the effectiveness of an experimental traffic routing plan or evacuation strategy. For example, evacuees in a specific community will be directed to an identified exit, or sub-set of exits from the endangered area

(Southworth, 1991). If the plan estimates evacuation time well, the third option may provide the best method to control the traffic evacuation. The fourth option allows for the expression of myopic evacuee behavior. The idea is that if the evacuees see considerable traffic congested ahead them, many will detour to find alternative routes to exit this endangered area. The assumption behind this option is that a portion of people know the road network well around the endangered area. As a matter of fact, all four methods may happen simultaneously in the face of a real regional evacuation (Southworth, 1991). And in this study, except the second method, the integrated simulation model would include the characteristics of the other three.

Despite these four qualitative methods for the evacuation destination selection, there are still some quantitative models to address this issue. The most common and widely-used model of destination selection is some form of spatial interaction model (Wilson, 1970). The format of the general model is as follows:

$$T_{ij} = N_i * P_{ij}$$

where T_{ij} represents the number of evacuees evacuating from originating point i to destination j. N_i is the number of people located in point i, while P_{ij} indicates the possibility of travelling from i to j. The description of P_{ij} is given below:

$$P_{ij} = W_j * f(c_{ij}) / \sum_j W_j * f(c_{ij})$$

Where W_j is a measure of the attraction potential of location j; and $f(c_{ij})$ is a function of the travel time associated with travelling from i to j.

Other than the model above, Sorensen and Mileti (1988) provided needed data, showing the percentages moving to relatives, friends, and to official shelter by selected evacuations.

2.1.2.4 Traffic Route Selection

One challenge for researchers is to find efficient ways to model and predict traffic flow. Route selection models are those models used to approximate the movement of evacuees over a transportation network, over time. Therefore, the route selection model is one of most important models in traffic simulation models. Due to the character of traffic, most of the decisions of route selection are not independent. Thus, in traffic systems the interdependence of actions leads to a high frequency of implicit coordination decisions (Klugl and Bazzan, 2004). Some methods (e.g. radio, Internet) exist to help the drivers to find an efficient path, but most of these methods do not consider the drivers decision making process. By considering this shortcoming, Klugl and Bazzan (2004) studied the influence of drivers' decision-making on the traffic system as a whole, and how simulation can be used to understand complex traffic systems. In spite of empirical studies on route choice behavior that have shown that drivers use numerous criteria in choosing a route, fastest path routing has typically been adopted in-route guidance systems because of its simplicity.

In recent years, because enumerating all non-dominated paths is computationally too expensive, many efficient shortest path methods have been developed (Handler and Zang, 1980; Huang et al., 2007; Park et al., 2007; Santos et al., 2007). Among them, Park et al.'s (2007) method is one of the most current and high-quality studies. The objective was to develop computationally efficient algorithms for identifying a manageable subset of the non-dominated (i.e., Pareto optimal) paths for real-time in-vehicle routing. However, obtaining a stable mathematical representation of the driver's utility function is theoretically difficult and impractical, and identifying the optimal path given a nonlinear utility function is a nondeterministic polynomial time (NP)-hard problem. Hence, they proposed a heuristic two-stage strategy that identifies multiple routes and then selects the near-optimal path in their study. The result showed that their algorithm can significantly reduce computational complexity while identifying reasonable alternative paths. Another good concurrent study that also considered shortest-path algorithm was done by Huang et al. (2007). In their paper, they proposed an incremental search approach with novel heuristics based on a variation of the A^* Algorithm-Lifelong Planning A^*. They also suggested using an ellipse to prune the unnecessary nodes to be scanned in order to speed up the dynamic search process. Their proposed algorithm determines the shortest-cost path between a moving object and its destination by continually adapting to the dynamic traffic conditions, while making use of the previous search results. Experimental results showed that the proposed algorithm performs significantly better that the well-known A^* algorithm.

Despite the advantages of some route selection studies that consider numerous criteria for the drivers, this study adopts the fastest path routing because of its simplicity.

2.2 Vehicle-Based Microsimulation of Evacuation

This section provides a detailed review from two aspects: 1) the characteristics of the vehicle-based microsimulation approach; 2) previous studies that have been conducted using microsimulation.

2.2.1 Basic Characteristics of Vehicle-Based Microsimulaion

Vehicle-based microsimulation is a model based on individual vehicle behavior for the purpose of assessing the traffic performance of highways and other road networks (Federal Highway Administration, 2005). Microsimulation can provide valuable information about the transportation system performance and the potential improvements to the analyst. There are mainly four basic models for the vehicle-based microscopic simulation: car-following model, lane-changing model, demand model, and routing model (Fu and Wilmot, 2004).

Figure 2.1 illustrates the basic principles of the car-following model created by Wiedemann, which is used by VISSIM™ (Planung Transport Verkehr, 2007). Two Wiedemann models (i.e. Wiedemann 74 and Wiedemann99) exist, and Wiedemann 74 is used in the local traffic, while Wiedmann 99 is used in highway traffic (Planung Transport Verkehr, 2007). The model takes into account both the physical characteristics (e.g. type) of vehicles and psychological characteristics of drivers during the car-following process. It assumes that when a faster vehicle approaches a slower vehicle on a single lane, the faster vehicles makes its decision on deceleration according to the perception threshold (SDV) which is determined by the distance and the speed difference between the two vehicles. After the following driver realizes that he or she is slower than the proceeding vehicle (OPDV is the action point in Fig.2.3), he or she then starts to accelerate again until reaches another perception threshold. Driver's aggressiveness can be modified by adjusting the values of the relevant thresholds (Chen, 2006).

The lane-changing model used in VISSIM models has two types of lane-changing behavior: mandatory lane change and freeway lane change (PTV, 2004). A typical mandatory lane change occurs when vehicles approach the next link on their route. Drivers make a freeway lane change when they desire more room or higher speed on adjacent lanes.

In addition to the driver behavior in the car-following and lane-changing processes, the demand model is another model for microscopic simulation. Since the 1960's, urban travel demand modeling has followed a four-step procedure: trip generation, trip distribution, mode choice, and traffic assignment (Oppenheim, 1995). As the first step in travel demand modeling, the traditional trip generation model estimates the number of trips as origins or destinations in each traffic analysis zone (TAZ). The analysis can be performed at two levels, disaggregate or aggregate. At the disaggregate level, trip estimation is based on the characteristics of households, such as income, household size, and number of licensed drivers in the household; while at the aggregate level the characteristics of the traffic analysis zone are used. Current practice in hurricane evacuation travel demand modeling is to conduct the process of estimating travel demand in two steps: the estimation of total evacuation demand and the estimation of departure time (Fu and Wilmot, 2004). Evacuation software packages can be grouped into two categories: those using static assignment and those using dynamic assignment procedures (Friesz et al., 1989; Ran and Boyce, 1996). The traditional static procedures do not give any information on the dynamics of the traffic, hence the dynamic method has become more and more used in the past 20 years.

Network routing problems can be classified based on two primary attributes, responsibility and communication. Responsibility refers to who is given ultimate responsibility for generating and assigning routes, while communication refers to the level of interaction between the supply (managers responsible for the network) and the demand (entities to be moved) in the network (Adler and Blue, 2002). Various approaches to network routing may be found in the literature related to evacuation. For instance, Dunn and Newton (1992) used a maximum flow approach to determine routes that will accommodate the greatest number of evacuees. The maximum flow approach aims to utilize the full capacity of each evacuation route, and while this approach may be applied to assess road capacity, it is not practical to apply the results to evacuation planning and management (Cova and Johnson, 2002).

Yamada (1996) used the minimum-cost flow problem (i.e. finding the cheapest possible way of sending a certain amount of flow through a flow network) to assign pedestrian evacuees to shelters at the city scale. Yamada (1996) defined the shortest evacuation plan (SEP) as one where the total distance from all evacuees to all shelters is minimized. For a pair of origins and destinations, the optimal route is updated dynamically according to traffic conditions en-route. The dynamic route assignments can only be incorporated into the microsimulation process, and are impossible in macrosimulation.

Most of the default settings for these models are used for the VISSIM ™ in this study because they have already been calibrated and validated.

2.2.2 Previous Studies on Vehicle-Based Microsimulation

Vehicle-based microsimulation for large-scale evacuation is very intensive computationally (Burghout et al., 2005). Therefore, few microsimulation studies of emergency evacuation have been done before the 1990s. Since the early 1990s, with the advent of newer computer technologies and more advanced software systems, there has been a surge of traffic flow studies using microscopic simulation modeling (Gomes et al., 2004).

Along with these studies, some traffic issues were studied and solved by using these microscopic simulation models. For example, to compute the minimum clearance time needed to evacuate all residents participating in an evacuation in advance and the number of residents needed to be accommodated if the evacuation route becomes impassable, Chen et al. (2006) conducted a microsimulation. Using 2000 US Census population data and the agent-based microsimulation software VISSIM to simulate the evacuation in the Florida Keys area, they found that the result from microsimulation is closer to reality than the result from macrosimulation. Cova and Johnson (2002) used microsimulation to study neighborhood evacuations in an urban-wild land interface in a controversial fire-prone canyon community east of Salt Lake City, Utah, and GIS was used to map the different evacuation time needed in the neighborhood. The results showed that both the neighborhood departure time and the mean number of vehicles per home have effects on the evacuation time over the entire neighborhood. From Chen et al. (2006) and Cova and Johnson’s (2002) studies above, it can be concluded that to minimize the m evacuation time it is important to stagger some given variables such as neighborhood departure time.

Other than the clearance time, microsimulation can also be used to simulate other traffic issues, such as optimizing the ramp performance control strategies (Beegala et al., 2005; Chang and Li, 2002), traffic signal control (Fang and Elefteriadou, 2006; Mirchandani and Head, 2001), dynamic of traffic flow with real-time traffic information (Yokoya, 2004; Benakiva et al. 1991).

Although vehicle-based microsimulation has many advantages and applications, there still exist some problems in the microsimulation modeling, and they limited its utilization scope. First, due to the detailed nature of the models, the preparation of input data (e.g. network coding and representation) can be very time-consuming and tedious. In addition, micro models are highly sensitive to errors or variation in input demand data, especially under congested conditions. Also, due to the complicated structure of the models involved, calibration of the model is not trivial. For these reasons, vehicle-based microscopic models are usually applied to smaller networks and may suffer from boundary effects (Burghout et al., 2005).

To overcome these drawbacks, some scientists tried to integrate microsimulation with macrosimulation or mesosimulation models. Burghout et al. (2005) presented a hybrid mesoscopic-microscopic model that applies microscopic simulation to areas of specific interest, while simulating a large surrounding network in lesser detail with a mesoscopic model. By applying the simulation model on a mixed freeway/urban network in the north of Stockholm, they divided the network into the meso part in the north (simulate by Mezzo), which consists mainly of freeways, and micro part in the south (simulate by MITSIMLab), which consists of complex intersections and signal controls. The simulation results showed that the proposed architecture is very promising. Sahraoui and Jayakrishnan (2005) also tried to integrate microscopic with macroscopic models for calibration/validation and path dynamics on large networks. However, these above-mentioned integrated models still use TAZ centroids as the origin and destination locations, which are sometimes not accurate to represent the detailed characteristics of residential area. Also, these models cannot change the destination for each vehicle dynamically in the whole simulation process according to the traffic situation in the evacuation situation.

2.3 Agent-Based Modeling

With the emergence of agent-based technologies, there is growing interest in modeling the spatial decision-making processes of the individuals who interact in the dynamic spaces and produce the space-time paths of mobile, geographically situated objects (Bennett and Tang, 2006). Agent-based models are particularly suitable for modeling complex systems, where many agents interact. The two basic components of agent-based modeling include a model of the agents as well as a model of their environments (Deadman, 1999). Because the agent-based models can represent individual's spatio-temporal behavior, they can provide unique insight in many fields, such as the social phenomena (e.g. individual income tax evasion and drinking behavior) (Bloomquist, 2006; Gorman et al., 2006; Gimblett, 2002), and ecological issues (e.g. the human and animals movement over large spaces; life histories of many thousands of individual planktons) (Ahearn et al., 2001; Woods, 2005). Among all those agent-based application studies, Xie et al.'s (2007) was the first to utilize agent-based modeling to predict urban sprawl. In their study, they propose the emergent phenomenon known as "desakota," the rapid urbanization of densely populated rural populations in the newly-developed world, particularly China, which can be simulated using agent-based models that combine bottom-up actions with global interactions. To prove their theory, they developed a simple logic that links local household reform to global urban reform, translating these ideas into a model structure that reflects these two scales. The model is implemented in RePast 3 software and is validated using a blend of data taken from remote sensing and government statistical sources.

Agent-based modeling is also been widely used in transportation field (Zhu et al., 2000; Bocker et al., 2001; Martijn and Heijden 2007). For example, because an efficient scheduling method is required to solve the real-time scheduling of full truckload transportation orders with time windows that arrive during schedule execution, Martijn and Heijden (2007) introduced an agent-based approach where intelligent vehicle agents schedule their own routes. They interact with job agents, who strive for minimum transportation costs, using a Vickrey action for each incoming order. This proposed agent-based method offers several advantages: it is fast, requires relatively little information and facilitates easy schedule adjustments in reaction to information updates. By using the railway transport system train coupling and sharing (TCS), Bocker et al. (2001) also developed a multi-agent-based scheduling system. This system involves the planning of travel units and the optimization of solutions. The planning process is implemented as an incremental anytime algorithm that is capable of integrating new task specifications into the ongoing planning process. The initial solution is then optimized by a simulated trading approach.

However, the most widely-used agent-based modeling in the transportation field is vehicle-based microsimulation, which can be regarded as an application of agent-based model because it fulfills all the qualifications needed (Adler and Blue, 2002; Dia, 2002; Chen et al., 2006). Two basic components form the core of the microsimulation vehicle-based model: network elements (the environment) and driver behavior (the agent) (Chen, 2006). The characteristics of the agents' travel/traffic environment include variables such as road category, traffic lights, and traffic signals, for which the data are generally available. It is also relatively easy to define the behavior rules for motorists' driving choices, such as rules regarding accelerating, decelerating, and lane changing (Chen, 2006). Adler and Blue (2002) proposed a route guidance system based on multi-agent negotiation between agents that represent network managers, information service providers, and drivers equipped with route guidance systems. This route guidance system allows a traffic management center to optimize the traffic control strategy continuously based on real-time information while offering the user advanced route planning and guidance which is responsive to current conditions. Their result showed that the multi-agent approach is a natural extension of the National ITS Architecture, and it is highly scalable and adaptable to a variety of networks and user populations.

2.4 Major Agent-Based Simulation Models in Transportation

With agent-based modeling techniques utilized in transportation simulation, each driver is always defined as an agent in the simulation model, and the road network is defined as the simulation environment. Together with the characteristic variables of both agents and environment, such as vehicle mode, road category, speed limit, and traffic signals, the agent-based model is ready to be executed. Otherwise, this kind of model is also relatively easy to define the behavior rules for motorists' driving choices, such as rules regarding accelerating, decelerating, and lane changing.

Because of the advantages of agent-based simulation model in transportation and advancements in computer technology in recent years, several software packages have been developed that are routinely applied to the study of traffic flowing. Each of these packages has pros and cons for simulating various types of traffic situations. No guidance is provided, however, on how to select appropriate simulators based on their capabilities and internal algorithms for analyzing specific simulation purpose. One of the most comprehensive reviews of the existing micro-simulation models was done in the SMARTEST project that was partially funded by the European Commission for Transport Research (Chen, 2006; Algers et al. 1997). Fifty-eight micro-simulation models have been identified in their study and thirty-two models have been analyzed (Table 2.1). Three types of organizations are involved in the design of micro-simulation models. They are in transportation research institutes, universities, and industrial organizations. Micro-simulation models are essentially research products. Among the micorsimulations models listed in Table 2.1, nine are commercial products (AIMSUN2, FLEXSYT II, FRESIM, HUTSIM, INTEGRATION, PARAMICS, THOREAU, TRAF-NETSIM and VISSIM) and are continuously in development. Three others can be obtained upon request (MIXIC, NEMIS and PHAROS with user agreement restricting use). Eleven are in development (AIMSUN2, ANATOLL, DRACULA, INTEGRATION, MELROSE, MITSIM, PLANSIM-T, SIGSIM, SISTM, SITRAS and VISSIM) (Chen, 2006). Based on traffic conditions, the models were grouped into four types by Algers et al. (1997): 1) for urban traffic; 2) for motorway traffic; 3) for a combination of urban and motorway traffic; and, 4) other models designed for every specific objectives (Table 2.2).

Models of the fourth type "other" were mostly designed for highly specific objectives such as the modelling of the tactical level of driving and the testing of intelligent vehicle algorithms (Chen, 2006). If the model belongs to the urban, motorway and combined types, then its objective is essentially to quantify the benefits of Intelligent Transportation Systems (ITS), primarily Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS). However, many of these three kinds of microsimulation models have been adapted to study the evacuation traffic flow, transportation operations, and strategies (Algers et al., 1997; Chen, 2006).

“Microsimulation is used for evaluation prior to or in parallel with on-street operation. So many objectives are covered, such as research on dynamic traffic control, incident management schemes, real-time route guidance strategies, assessment of the impact and sensitivity of alternative design parameters (number of lanes, length of ramps, road curvatures and grades and lane change regulations), adaptive intersection signal controls, ramp and mainline metering, toll plazas, and lane control systems (lane use signs, electronic toll collection, high occupancy vehicle lane, etc.)” (Algers et al., 1997).

Table 2.1. Microsimulation models (Source: Algers et al. 1997; Chen, 2006))

Model	**Country**	**Model**	**Country**
AIMSUN2	Spain	NEMIS	Italy
ANATOLL	France	NETSIM	USA
AUTOBAHN	Germany	PADSIM	UK
CASIMIR	France	PARAMICS	UK
CORSIM	USA	PHAROS	USA
DRACULA	UK	PLANSIM-T	Germany
FLEXSYT II	Netherlands	SHIVA	USA
FREEVU	Canada	SIGSIM	UK
FRESIM	USA	SIMDAC	France
HUTSIM	Finland	SIMNET	Germany
INTEGRATION	Canada	SISTM	UK
MELROSE	Japan	SITRA-B+	France
MICROSIM	Germany	SITRAS	Australia
MICSTRAN	Japan	TRANSIMS	USA
MITSIM	USA	THOREAU	USA
MIXIC	Netherlands	VISSIM	Germany

Table 2.2. Four types of models for transportation analysis (Source: Algers et al. 1997; Chen, 2006)

Urban	**Motorway**	**Combined**	**Other**
CASIMIR	AUTOBAHN	AIMSUN2	ANATOLL
DRACULA	FREEVU	CORSIM	PHAROS
HUTSIM	FRESIM	FLEXSYT II	SHIVA
MICSTRAN	MIXIC	INTEGRATION	SIMDAC
NEMIS	SISTM	MELROSE	
NETSIM		MICROSIM	
PADSIM		MITSIM	
SIGSIM		PARAMICS	
SIMNET		PLANSIM-T	
SITRA-B+		TRANSIMS	
SITRAS		VISSIM	
THOREAU			

Another recent review of microsimulation models described interchanges traffic simulation (Fang and Elefteriadou, 2005). They focused on identifying the elements that should be available in a simulator to evaluate a specific interchange scenario (including type, geometry and traffic control characteristics) in their study. The paper does not identify all the specific packages that are appropriate for a specific scenario these evolve constantly; even though the current version of a package may not support a particular function, future versions of that package may incorporate it. Thus, identifying the most appropriate package would very quickly become obsolete. They thought that it is up to the analyst to examine whether a particular characteristic or algorithm is present in a specific package. To accomplish this, three simulators (AIMSUN, CORSIM, and VISSIM) were selected and studied (Fang and Elefteriadou, 2005). After simulation by using these three models, they concluded that several elements are identified as critical in simulation interchanges, which fall in the following categories: 1) the capability to represent of specific geometric characteristics; 2) the capability to simulate specific signal control plans; 3) calibration needs and accuracy in comparison to field conditions; and 4) the extraction of specific performance measures from the simulator.

Among all these microsimulation models, the most widely applied microsimulation software packages for traffic flow modeling and emergency situations are: 1) TSIS/CORSIM; 2) Paramics; and, 3) VISSIM (Chen, 2006). The first model, CORSIM, was developed by the U.S. Federal Highway Administration in the 1970s and has been used for over thirty years (Chen, 2006), and it is run within a software environment called the Traffic Software Integrated System (TSIS), which provides an integrated, Windows-based interface and environment for executing the model. A key element of TSIS is the TRAFVU output processor, which allows the analyst to view the network graphically and assess its performance animation. CORSIM is a microscopic simulation model designed for the analysis of freeways, urban, streets, and corridors or networks. The model includes two predecessor models: FRESIM and NETSIM. FRESIM is a microscopic model of freeway traffic, and NETSIM is a model of urban street traffic. CORSIM is a link-node based network model, and its capabilities include simulating different intersection controls (Bloomberg and Dale, 2000). CORSIM has been applied to evacuation study from various perspectives. Gu (2004) integrated the regional transportation planning package TRANSIMS with CORSIM to perform sub area traffic evacuation analysis. Gu (2004) used and applied the evacuation model to Virginia Tech main campus, Blacksburg, VA to evaluate this sub area. To testify the effectiveness of contraflow in the situation of evacuation, Lim and Wolshon (2005) assessed and compared the operational characteristics of contraflow evacuation termination point designs that would be used under threat from catastrophic storms by utilizing CORSIM to model contraflowing freeway traffic under evacuation conditions. Also from the perspective of employing contraflow traffic, Theodoulou and Wolshon (2004) also used CORSIM to model the freeway configuration that will be used to evacuate New Orleans as well as two alternative scenarios for this same segment.

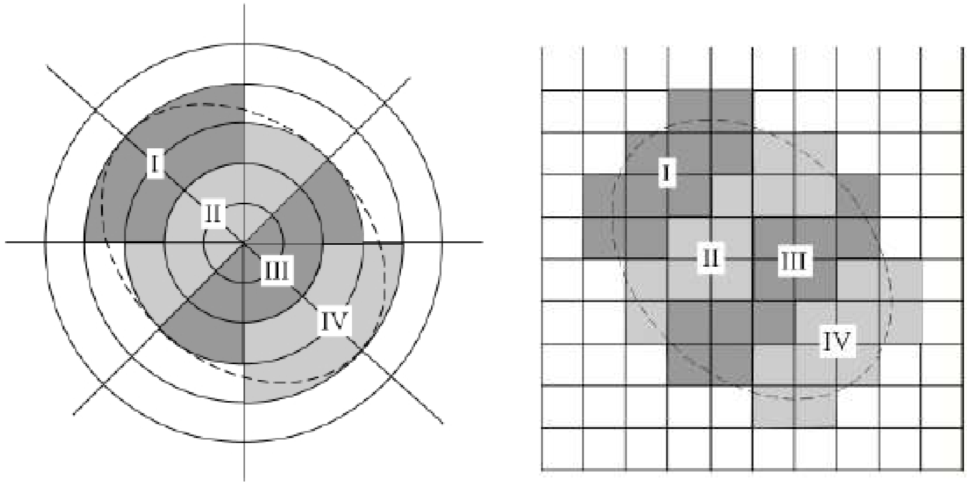
The software package, Paramics, was born out of a University of Edinburgh project in the early 1990s. Staff from the project then founded Quadstone Limited. As one of the UK's leading independent software companies, Quadstone developed a commercial version of the Paramics software to become one of the leading microscopic simulation packages in the world (Quadstone, 2002). There are also many applications of using Paramics to study the different aspects of evacuation. For real time traffic management under emergency evacuation, Liu et al. (2007) presented a model reference adaptive control (MRAC) framework. Because of the highly unpredictable feature of evacuation traffic flow, they proposed to use a microscopic traffic simulation model to implement the short-term traffic control strategy at the decision nodes based on the splitting rates. In particular, they adopted Paratics as their evaluation tool. Another widely referenced study was done by Cova and Johnson (2002) who used Paramics to test neighborhood evacuation plans in an urban environment, and assess the effects of a proposed second access road on household evacuation time. Paramics was also used to investigate the effectiveness of simultaneous and staged evacuation strategies (Chen and Zhan, 2008). They also conducted simulations using Paramics on three types of road network structures under different population densities. The three types of road network structures include a grid road structure, a ring road structure, and a real road structure from the City of San Marcos, Texas.

VISSIM is a microscopic, time step and behavior based simulation model developed to analyze the full range of functionally classified roadways and public transportation operations, so it is the ideal tool for transportation professionals who want to simulate different traffic scenarios before starting implementation. VISSIM can model integrated roadway networks found in a typical corridor as well as various modes consisting of general purpose traffic, buses, light rail, heavy rail, trucks, pedestrians, and bicyclists (Bloomberg and Dale, 2000). VISSIM was developed by Planung Transport Verkehr (PTV) based on the work of Wiedemann at the University of Karlsruhe in Germany, and it has been applied to traffic analysis.

2.5 Staged Evacuation

After issuing the evacuation order, the traffic volume will surge rapidly and can cause congestion. Because we can make a statistical assumption that the aggregate distribution of originating vehicles in a neighborhood follows a Poisson distribution (Cova and Johnson, 2002), if a decrease in the peak originating vehicle number occurs, it should mitigate the traffic congestion. One feasible way to solve this problem is to use a staged evacuation strategy rather than simultaneous evacuation. In simultaneous situation, all residents in the affected area are informed to evacuate simultaneously; whereas, in staged evacuation, residents in different zones (Chen, 2006) are organized to evacuate in a sequence. Very few studies have examined staged evacuation before, and the most famous one was done by Chen (2006). She divided the affected area into four parallel zones, and divided them into two groups. The starting evacuation time has a time gap among each group. Two sets of general road networks for testing the effectiveness of simultaneous and staged evacuation strategies were used. One is a simulated grid network and the other is a simulated ring road network (Fig. 2.3(a), 2.3(b)). The simulation result showed that there exist some staged strategies that can reduce the whole evacuation time in both grid and ring road network. With this conclusion, she also investigated this conclusion further on Galvestion County, Texas, which has a larger and real road networks. A link-node based traffic analysis model was developed to estimate the network clearance time. The simulation results showed that the simultaneous strategy used an average of 16.65 hours to evacuate, while the best staged evacuation strategy only used 15.67 hours to evacuate. The precondition of this result was that the traffic can be congested if under simultaneous strategy.

However, the only purpose in Chen’s study is to minimize the network evacuation time, and she didn’t consider the different situations (e.g. social and biophysical vulnerability) among neighborhoods at all. Even so, the four paralleled evacuation zones were partitioned arbitrarily in her study.



(a) (b)

Figure 2.3. Simulated road networks used in the simulation and the division of the four zones in the affected area: (a) grid road network, (ring road network). (Note: ellipse – hypothetical affected area, solid lines – road networks) (Source: Chen, 2006)

Chapter 3 . The Creation of an Integrated Agent-Based Microsimulation Model to Study Regional Area Disaster Evacuation

3.1 Introduction

With the threat of continuous global warming (Intergovernmental Panel on Climate Change Fourth Assessment Report, 2007), the number and intensity of tropical cyclones such as hurricanes are expected to increase in some regions (Walsh, 2004). In 2005, there were 14 hurricanes (a new record) in the Atlantic Basin, three of which were among the most powerful and costly in the 154-year history of record-keeping in the region (Wolshon, 2006). Southern Louisiana, situated along the Gulf of Mexico, is one of the most hurricane-vulnerable areas. In less than three years, it was hit by four devastating hurricanes, Katrina and Rita in 2005, and then in 2008 directly by Gustav and indirectly by Ike.

When severe hurricanes approach, evacuation of people to a safer area is the first priority. Disaster evacuation simply involves moving people away from the endangered areas. However, evacuations in a real situation, particularly evacuations on a massive scale, are complex undertakings and difficult to plan (Wolshon, 2006). An evacuation order that starts too late or takes too long to complete will most likely lead to higher casualties and greater property damage. On the other hand, an evacuation order that starts too early could add unnecessary inconvenience and cost to most evacuees and is prone to error due to hurricane's likely change of course before landfall. Mass evacuation of urban areas due to hurricanes is a critical problem that requires extensive basic and applied research.

One of the most important factors influencing the outcome of a natural disaster in terms of human loss and property damage is the evacuation time, which includes three components: initial warning time, individual preparation time, and network clearance time. Initial warning time is the time period between the first notification of an existing potential hazard or natural disaster and the time when the order to evacuate is issued. The individual's preparation time is the time frame immediately following the issuance of an order to evacuate and the final decision to leave the dangerous area. The network clearance time is the time required to clear all evacuating vehicles from the roadways, which begins when the first evacuating vehicle enters the road network and ends when the last evacuating vehicle reaches its destination. This also includes the time spent by evacuees waiting along the road network due to traffic congestion (Jamei, 1984). The focus of this study is on the network clearance time. Specifically, the goal was to find the time required to evacuate all the residents in a hurricane-threatened region.

A number of simulation models have been developed to estimate the time required to clear a residential neighborhood if an evacuation order is issued. Vehicle-based microsimulation modeling, which focuses on the characteristics of individual motorist and travel behavior, has been widely used, as it often leads to the most accurate result (Hoogendoorn and Bovy, 2001; Chen, 2006). However, because detailed driver response modeling and path processing must be incorporated, applications of these vehicle-based microscopic models have been limited to simulate only small- to medium-sized urban areas. Few studies have attempted to address problems associated with mass evacuations using vehicle-based microsimulation at a regional scale (Sahraoui and Jayakrishnan, 2005). Another problem of vehicle-based microsimulation models for disaster evacuation is that the trip generation is based on the origin-destination (OD) matrix input, which may deprive the dynamic destination choice for each vehicle, and the matrix may also be too complex if too many origin-destination pairs exist.

Since for regional evacuation simulation, the time consumption is mostly caused by the complex local road network simulation, it is possible to reduce the simulation time for regional evacuation by combining two models, one for highway and the other for local traffic. This paper proposes the use of a two-level approach by separating the road network of the study region into two parts, highways (i.e. interstate highways and causeways) and major local roads. The local road network simulation was generated by a census block centroid-based microsimulation model developed for this study, whereas an existing vehicle-based microsimulation model, VISSIM™, was adopted to simulate the highway part of the road network (Planung Transport Verkehr AG, 2007). Both of these models are agent-based models, so they possess the advantages of agent-based models. The hurricane evacuation of New Orleans was simulated. The performance of the integrated simulation model in regional evacuation simulation is evaluated in terms of simulation running time and accuracy (i.e., ability to approximate real evacuation traffic data).

3.2 Study Area and Data Requirement

The study area in this study is the New Orleans region, a highly populated urban area in Louisiana, USA. It includes parts of St. Bernard, Orleans, Jefferson, and St. Charles Parishes (Figure 3.1). This area is bordered by Lake Pontchartrain to the north and the Gulf of Mexico to the south. There are over one-half million vehicles and a population over one million in this area.

New Orleans has long been considered “a disaster waiting to happen” area (Wolshon, 2006). Evacuating this city is difficult because New Orleans is bounded on the north by the lake, which limits the routes out. In the last 10 years, there were already four major evacuations, 1998 for Hurricane Georges, 2004 for Hurricane Ivan, 2005 for Hurricane Katrina, and 2008 for Hurricane Gustav. The interstate highway road network configuration (e.g. contraflow) for Hurricanes Katrina and Gustav, which will be used in this study, includes three evacuation directions (i.e. east, west, and north). The data used include the 2000 census data at the census block level, the Google™ online map, and the traffic-count data (Wolshon, 2006).

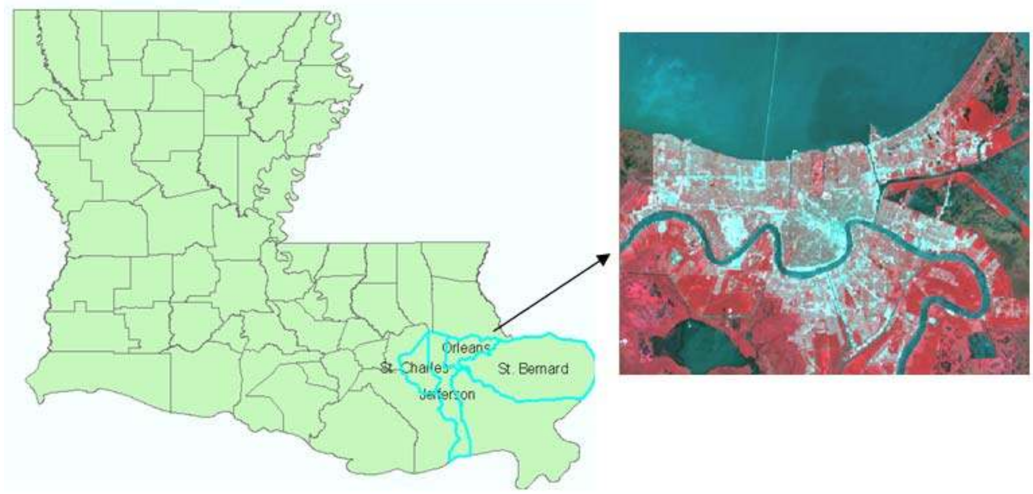


Figure 3.1.The study area and its remote sensing image (Landsat 5 TM 2002 image)

The traffic-count data were recorded as part of the Louisiana Department of Transportation and Development (LA DOTD) traffic monitoring network to show the traffic volumes at every station throughout the state. Data are available even on lightly travelled roads through sparsely-populated areas hundreds of miles from the storm landfall location (Wolshon, 2006). The traffic capacity data (which record the maximum traffic per unit of time that a given road segment can carry under specified conditions) and the speed limit on each road segment were obtained from the New Orleans Regional Planning Council.

3.3 Census Block Centroid-Based Microsimulation Model Preparation

The first part of the proposed integrated model is the census block centroid-based microsimulation model, which is used to simulate the local part of traffic flow. This part of the model is the major focus for this proposed model since the other part of the integrated model is VISSIM™, a piece of commercially available software. The census block centroid-agent-based microsimulation model is expected to perform well for the local traffic simulation in a massive disaster evacuation because of improvements in accuracy of origin locations as input, dynamic destination choice, and shorter simulation time. The model was programmed in MATLAB™. There is one raster input layer in this agent-based microsimulation model, which is the local major road network layer, with three attribute tables for road links, nodes (i.e. intersections), and agents. Other simulation parameters could be added before model simulation. The mechanism of this census block centroid-agent-based microsimulation model is shown in Figure 3.2.

3.3.1 Road Link Attributes

Only the major road network was included in the census block centroid-based microsimulation model. The road network was digitized from the Google Maps™ (maps.google.com). Figure 3.3a shows the highway network in black and the local road network in red.

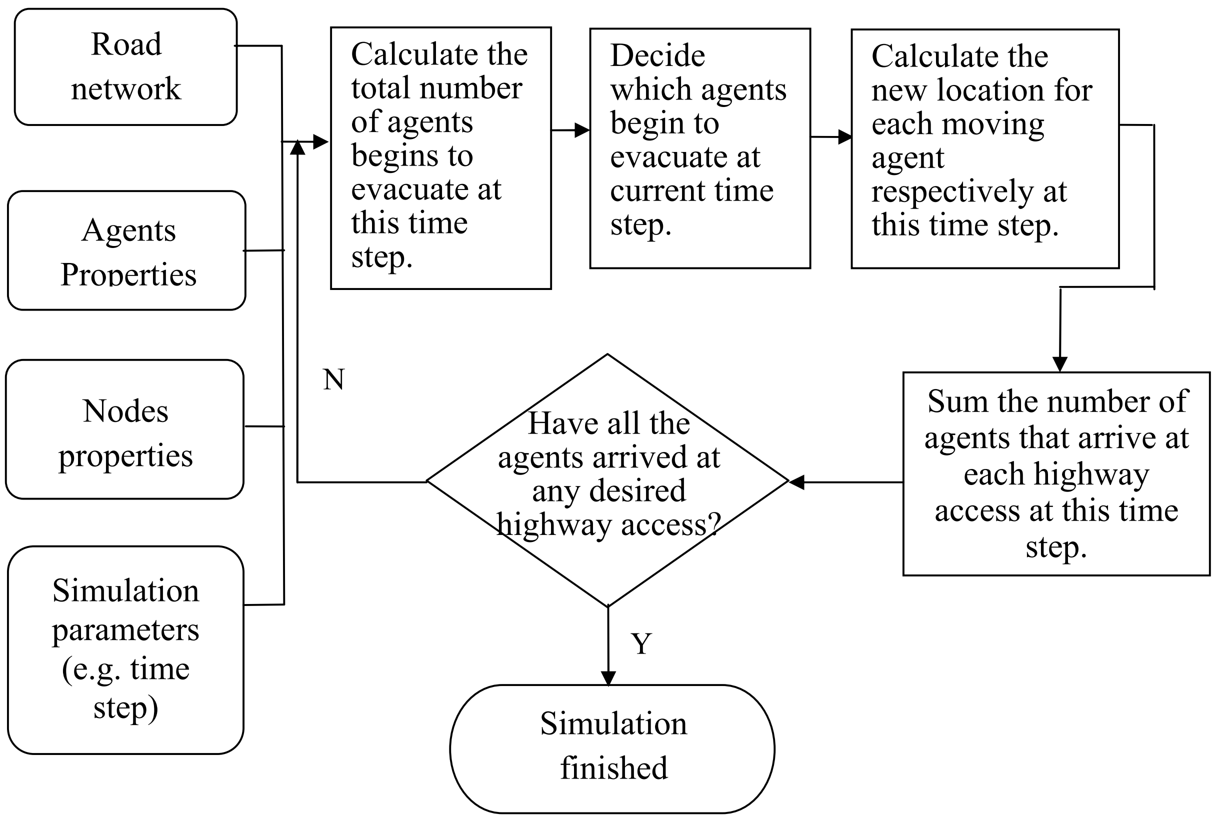
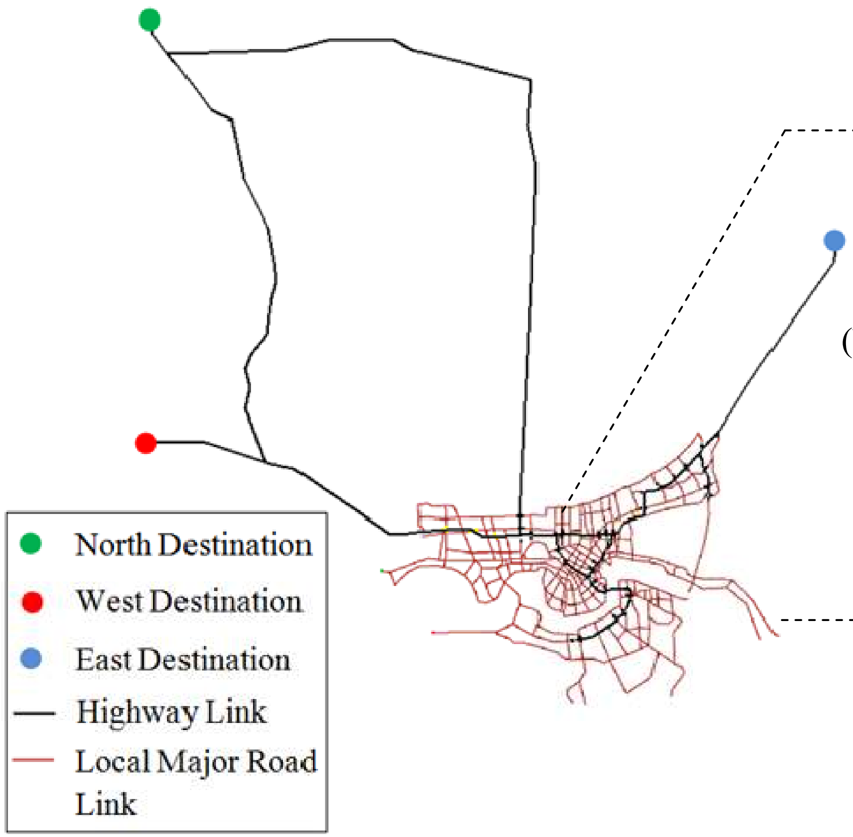
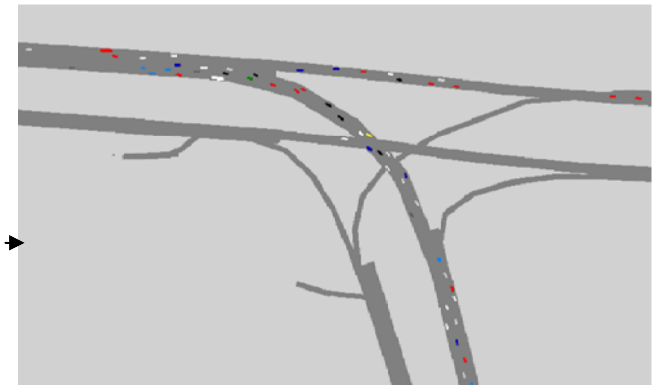


Figure 3.2.The mechanism of census block centroid-agent-based microsimulation model (for local road network simulation)





(b) Detailed highway traffic simulation at the 27^{th} hour

(a) Highway and major road network in the study area

(c) Local traffic simulation at the 27^{th} hour

Figure 3.3. Road network and one simulation snap

The attributes for each major road segment (i.e., link) include: length, speed limit, (maps.google.com). Figure 3.3a shows the highway network in black and the local road network in red.

The attributes for each major road segment (i.e., link) include: length, speed limit, capacity-AB, capacity-BA, start node ID, end node ID, current total number of vehicles, current speed-AB, and current speed-BA. Capacity-AB and capacity-BA are the capacity for each direction of the road segment AB, whereas start node ID and end node ID are the ID numbers of the two ends of the road segment. The driving speed (speed-AB or speed-BA) for all the agents on one single link with the same driving direction is the same. In traditional static models, the travel speed along a road is a fixed value that can be calculated by a number of factors. These factors include the traffic volume, road capacity, and free flow speed (Meyer and Miller, 1984). The relationship between the travel speed and the factors can be expressed by the following equation, developed by the Bureau of Public Roads (Jamei, 1984):

$$V = V_0 / [1+0.15*(A/C)^4] \qquad (1)$$

where V is the travel speed of vehicle moving along the subject road, V_0 is the speed limit of the subject road, A is the traffic volume, representing the static traffic volume that would pass through the road throughout the simulation process, and C is the practical capacity of this link.

Since the simulation model is a dynamic agent-based model, the travel speed along a road is calculated and changed every time step. Also, the road link length L (unit: km) should also be considered as a factor affecting travel speed. Hence, equation 1 was modified as follows:

$$V = V_0 / \{1+a*[A/(C*L)]^b\} \qquad (2)$$

where A is the traffic volume to be defined as the current number of vehicles driving on the road link, a and b are now coefficients that need to be manually tuned for different simulation environments, instead of having fixed values as in equation 1.

3.3.2 Node Attributes

Nodes are the end points (i.e., intersections) for each road segment. The attributes for each node include locational coordinates, node Ids, node type (whether it is an exit for highway entrance or non-exit node), and the distance (i.e., travel time) to the nearest exit node for every evacuation direction. Because of the usage of contraflow in New Orleans, not all of access nodes can head for all final evacuation directions (i.e. east, west, and north). This means that some interstate highway access nodes can only head for one or two but not all three final evacuation directions. The possible final evacuation directions for all the highway access nodes are shown in Figure 3.4.

When any agent decides the next driving link on arrival at a node in the dynamic simulation process, the time of driving to the nearest exit node with desired evacuation direction will be recalculated for each node by using the Dijkstra's algorithm (to be discussed in a later section) based on the current traffic condition at each time step. And then when an agent arrives at one node, the model will compare the different values of "driving time to the nearest highway access" for each directly connected node. At that point, the agent would choose and drive on the road with "the minimum driving time to the nearest highway access". In the New Orleans metropolitan area, there are a total of 310 nodes for the local major road network.

3.3.3 Agent Attributes

The first step to build an agent-based microsimulation model is to find the initial location for each agent. Different from the traditional vehicle-agent-based microsimulation models, which often use the traffic analysis zone (TAZ) centroids to represent the initial

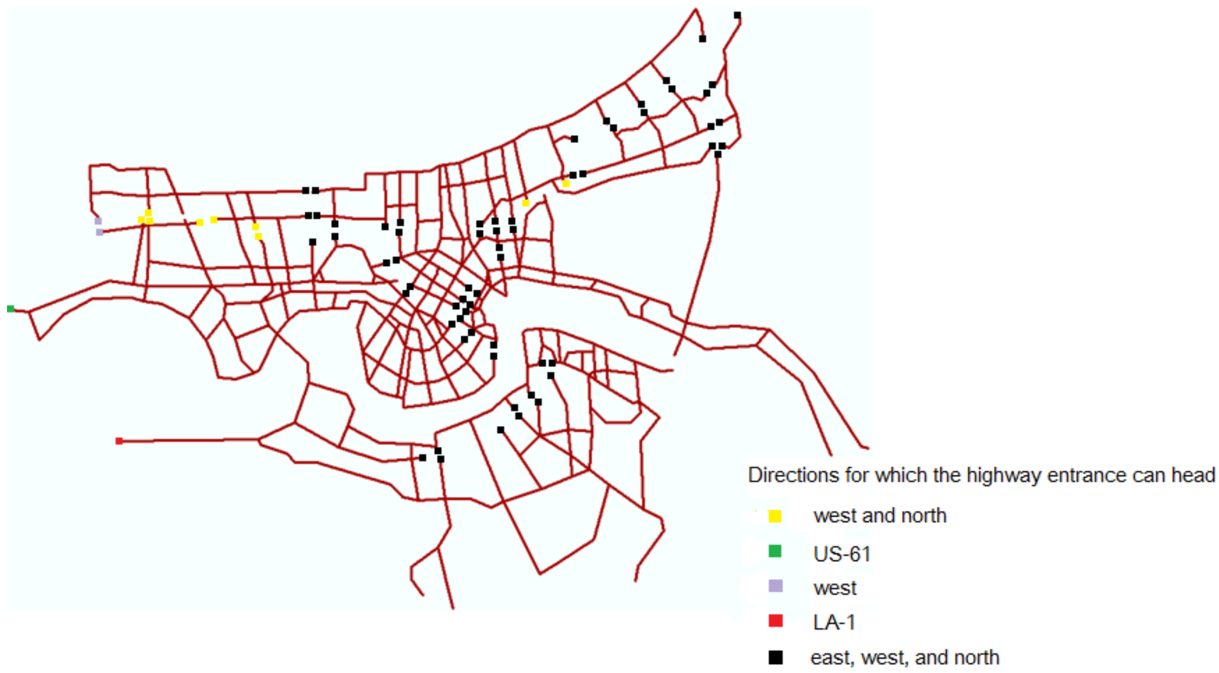


Figure 3.4.Highway entrances in New Orleans and their categories classified by using different available evacuation directions

locations of all the vehicles in the same TAZ (Miller Consulting, 2001), this model uses smaller units, the census block centroids, as the starting locations for the agents. This improves the starting location accuracy of the simulation model. There are about 300 TAZs in New Orleans metropolitan area, compared with 17,744 census blocks (Figure 3.5). The attributes for each agent include *locational coordinates*, *number of vehicles in the block*, *the road ID the agent is driving on*, and *the final evacuation direction* (i.e. east, west, north, US-61, or Louisiana Highway-1). In this study, there is one agent for each census block, and each agent is weighted by the number of vehicles in each block that participate in the disaster evacuation. The number of vehicles owned by each census block, a variable that is available from the census 2000 data, was used to multiply the participation rate (see section 3.4.1 below) to derive the number of vehicles that participated in evacuation.

3.4 The Census Block Centroid-Based Microsimulation Model Components

This study presents a new scheme that integrates a vehicle-based microsimulation model with a census block centroid-based microsimulation model to find the best regional simulation solution, in terms of higher model accuracy and shorter model running time. The modeling process includes five steps, namely the creation and calibration of: 1) traffic generation sub-model; 2) demand sub-model; 3) destination selection sub-model; 4) routing sub-model; and 5) a user specified plan set-up, analysis, and revision procedure (Southworth, 1991). Description of each modeling step is presented below. Also, the technical structure of this proposed model developed in MATLAB™ is described in Appendix A.

3.4.1 Traffic Generation Sub-Model

The traffic generation sub-model estimates the number of evacuees/vehicles in evacuation. Given the complexity of this issue, the number of vehicles to be loaded onto the highway network is often derived from a wide range of survey data (Southworth, 1991). For a

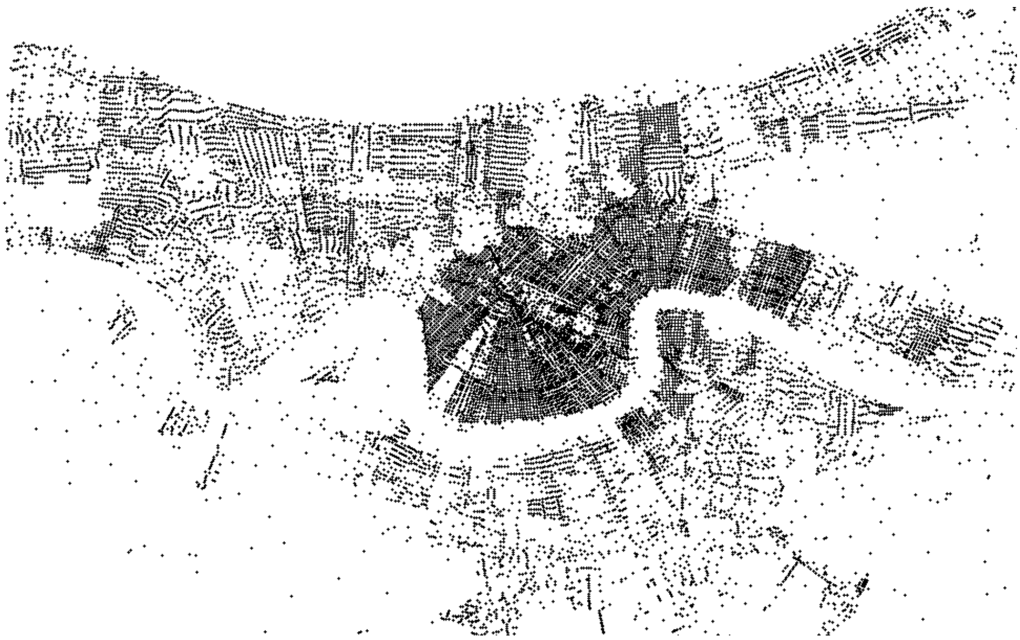


Figure 3.5.Census block centroids in New Orleans

severe disaster evacuation, such as a Category 4 or 5 hurricane, most of the residents who live in the disaster-threatened area must be evacuated before hurricane landfall. Therefore, in this kind of disaster situation, if the population in this region does not change greatly, the number of evacuees participating in disaster evacuation should not fluctuate too much each time. This means that the traffic count data from previous hurricane evacuations as means of validation in this simulation study.

Among the most recent disaster evacuation traffic count data available in New Orleans is that from Hurricane Katrina, obtained from Louisiana Department of Transportation and Development (LA DOTD). This count data was used to extract the number of vehicles for each evacuation direction. Hurricane Katrina weakened before making landfall as a Category 3 storm on the morning of 29August 2005 in southeast Louisiana. The traffic count data graph in LaPlace on I-10 west (Figure 3.6) shows that from 27 August to 28 August, there was more traffic volume in New Orleans than normal. Therefore, for each final evacuation direction, all the traffic volume from 27 August at 12:00am to 29 August at 4:00am was included across the count meter for that direction as the number of vehicles that participated in evacuation. New Orleans has five primary final evacuation directions, including three interstate highway final evacuation directions (east, west, and north) plus one US highway (US-61-North) and one LA highway (LA-1-West). The three interstate evacuation routes are: east through I-10 into Mississippi State; west through I-10 into Baton Rouge, LA, or Houston, TX; north through I-55 into Mississippi. For Hurricane Katrina, the number of vehicles for east evacuation was 41,540, which was recorded at Slidell, LA on I-10. The number of vehicles for west evacuation was 72,162, which was recorded at Laplace, LA on I-10. The number of vehicles for north evacuation was 53,434, which was recorded at Fluker, LA on I-55. The number of vehicles for US-61 evacuation was 43,587, which was recorded at Laplace, LA on US-61. For LA-1,

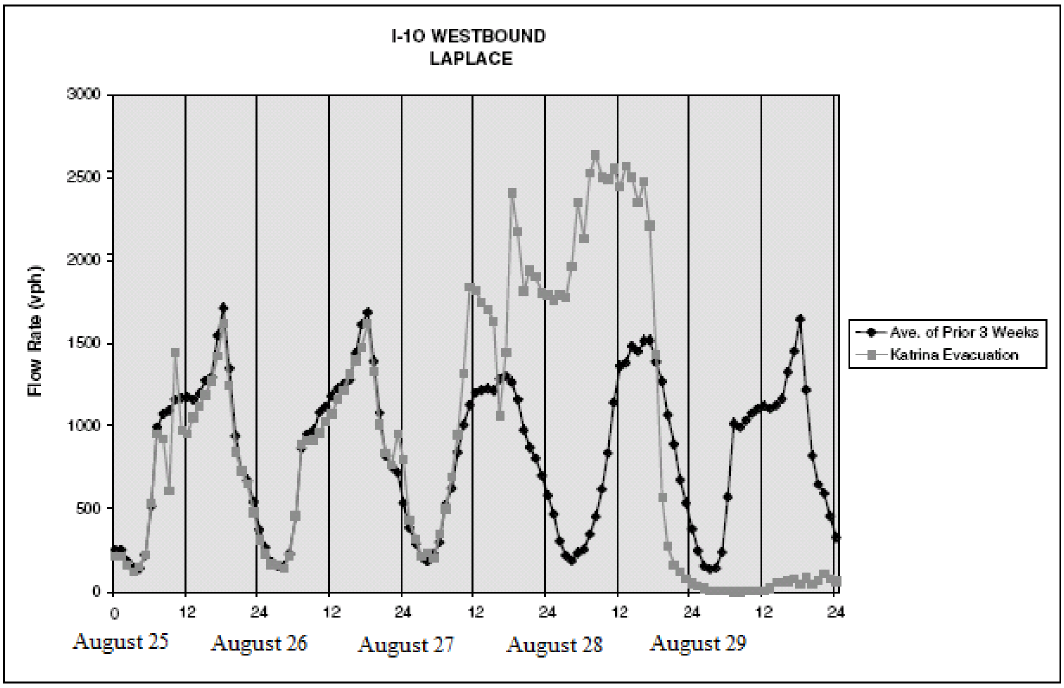


Figure 3.6.Traffic count data on westbound I-10 during Hurricane Katrina (LaPlace, Louisiana) (Monitor Date: 25 August, 2005-29 August, 2005; Source: Wolshon, 2006)

several traffic count meters recorded the number of passing vehicles, but none of them is near the New Orleans metropolitan area. So these count data for LA-1 cannot be used as input data for the simulation model. Instead, we acquired the estimate for LA-1, which was about 29,528 vehicles, from Post, Buckley, Schuh and Jernigan Inc. (PBS&J) (Theodoulou and Wolshon, 2004), a contractor of the New Orleans District of the USACE. As a result, the total number of vehicles that participated in evacuation in the New Orleans metropolitan area was 41,540+72,162+53,434+43,587+29,528=240,251. This number was used in the simulation.

The model assumes that issuing the evacuation order at any time of the day does not affect the traffic generation pattern. This means that the loading rates of all the evacuees are the same no matter when the evacuation order is issued. The model also does not take into consideration of the vehicle utilization rates and location specific populations (such as at home population, at work population, at school population, and special facility populations). The model simply adds all the number of vehicles in every census block of the study area, which was 524,266, as the total number of vehicles owned in New Orleans. Then, the vehicle participation rate (45.8%) for evacuation in New Orleans was calculated by using the number of total vehicles in New Orleans (524,266) divided by the number of vehicles that participated in Katrina's evacuation (240,251). Further, the model assumes that the participation rate for each agent to be the same, so by using the number of vehicles of a given census block and multiplying it by 0.458, we can get the number of vehicles expected to participate in disaster evacuation for each agent. With 17,744 agents in the study area, the average number of vehicles represented by each agent was about 13.54.

3.4.2 Demand Sub-Model

In the face of a disaster, evacuation timing is closely related to the behaviour of evacuees, who repeatedly evaluate their risk and make a decision of whether to leave or not

(Mei, 2002; Fu, 2004). The trip productions in the simulation time interval represent the traffic volume to be loaded onto the network in this period. Jamei (1984) suggested that the cumulative traffic volume plotted over time takes an 'S-shape' curve with a low loading rate at the beginning, and as time progresses the rate increases until it reaches its maximum threshold around halfway from the total loading period, as represented by equation 3:

$$R = 1/ \{1+\exp [-z*(t-T)]\} \quad (3)$$

Where R is the cumulative percentage of the total traffic loaded onto the network at the "clock" time, i.e., the loading rate. T represents the clock half-loading time since the start of the evacuation simulation run. In this study, T is equal to 26, half of the clearance time which is 52 hours from Aug 27th 2005 at 12:00am to Aug 29th 2005 at 4:00am. The current clock time in the simulation run is referred to as t, and it is incrementally increased at each time interval. The time interval was set by the model user before execution of the simulation model. A shorter time interval value would generally lead to more accurate simulation results, but would increase the model running time. Therefore, to make the simulation result reliable but not too time consuming, several different time intervals were tested and finally 30 seconds was selected as a reasonable value for the simulation time interval.

The z parameter in equation 3 is the slope of the logistic curve, which represents the response of the public to the disaster. There are three shapes: fast, medium, and slow (Figure 2.1). The fast curve, implying a higher z value, represents the quick response of the public to the disaster which could be a result of less available time for evacuation or probably late warning by the officials. The medium curve represents the predominant response that was obtained from the stated responses by individuals involved in actual evacuation. Finally, the slow curve, with a lower z value, represents the more available time for evacuation due to a natural disaster that could be forecasted many hours before its occurrence. Based on previous study, values of 0.04, 0.022, and 0.01 were initially used for fast, medium, and slow curves, respectively (Jamei, 1984). However, test runs show that these values only fit certain-period evacuation cases (e.g., total evacuation time around 8 hours). In a regional evacuation scenario which would take over 20 hours, these values should not be used to define the shape of the loading curve. So, an additional set of values, which were obtained from the following section, should be used for this case.

However, equation 3 does not consider the different loading rates for daytime and night-time. From the Hurricane Katrina traffic count data graph (Figure 3.6), the evacuation traffic volume clearly decreased during night-time. Hence, equation 3 was modified by adding the parameter *Y* to approximate trip productions at different times of the day, where *Y* values change according to the time of the day:

$$\begin{cases} Y = c * \sin((\text{arsine}(c/c) - \text{arcsine}(d/c)) / (12*60) * a + \text{arcsine}(d/c)) & (4) \\ \quad \text{(when 0:00am} < a <= \text{12:00pm)} & \\ Y = c * \sin(((\text{arcsine}(d/c) - \text{arcsine}(c/c))/719) * a + 2*\text{arcsine}(c/c) - \text{arcsine}(d/c)) & (5) \end{cases}$$

(when 12:00pm < a <=24:00pm)

The derivation of equations 4 and 5 are listed as appendix B. *c* and *d* are the value range of the sine wave that needs to be calibrated. The new loading equation then becomes:

$$R = 1/ \{1+\exp [-z*(t-T)*Y]\} \qquad (6)$$

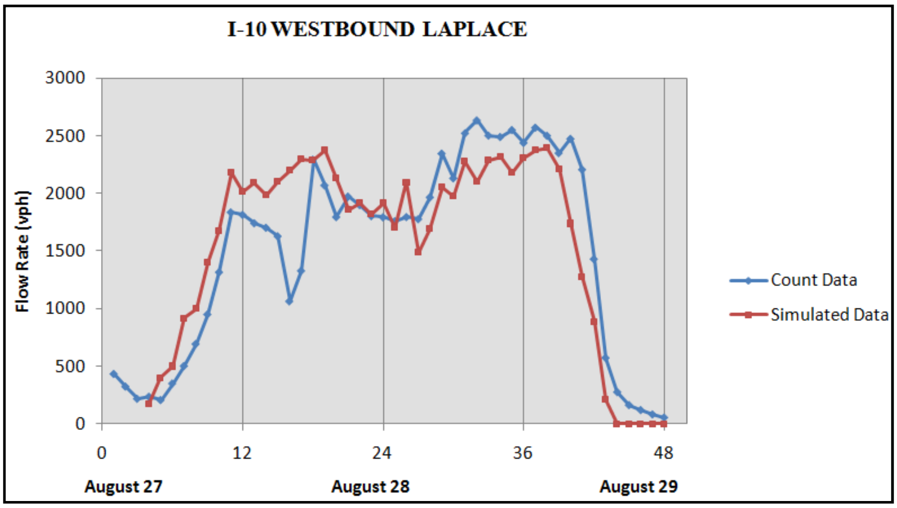
As a result, there are 3 variables (*z, c*, and *d*) that affect the loading rate *R.* The number of agents starting to evacuate during each time interval can be obtained by multiplying the corresponding loading rate with the total number of agents (i.e., total number of census block centroids).

Also from the traffic count data, the actual 24-hour cycle of the loading sine curve is not just from 24:00am to 24:00pm within a single day. It has a roughly 3-hours delay. This means that every cycle of the loading sine curve is from 3:00am of the first day to 3:00am of the next day. To incorporate this pattern into the loading rate model, we simply shifted the traffic simulated data curve 3 hours to the right (Figure 3.7) to fit it with the actual traffic count data curve.

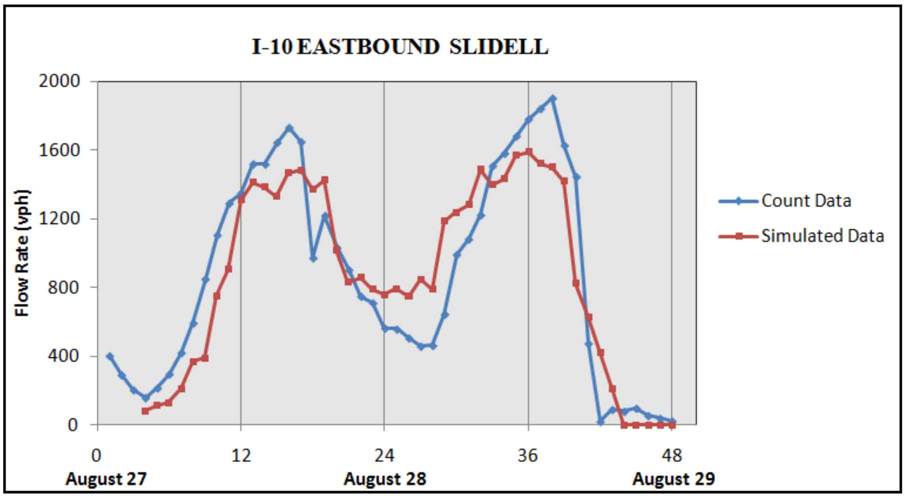
3.4.3 Destination Selection Sub-Model

There are two levels of destination selection decisions for each agent to make. In the first level, each agent must decide which final destination (i.e. east, west, north, US-61, or LA-1) it should target. This final destination for each agent is decided at the initialization phase of evacuation simulation, and it cannot be changed throughout the simulation process. In the second level of destination selection, each agent should decide which highway access node it should target. Since there may exist several highway entrances that can enter the highway traffic and arrive at the same first level final destination, the criterion of nearest highway entrance was used to determine the second-level destination. This second-level destination selection for any agent is changed dynamically at any time in the simulation process. An agent chooses a second-level destination at the beginning of its evacuation, but may change it based on the current traffic situation.

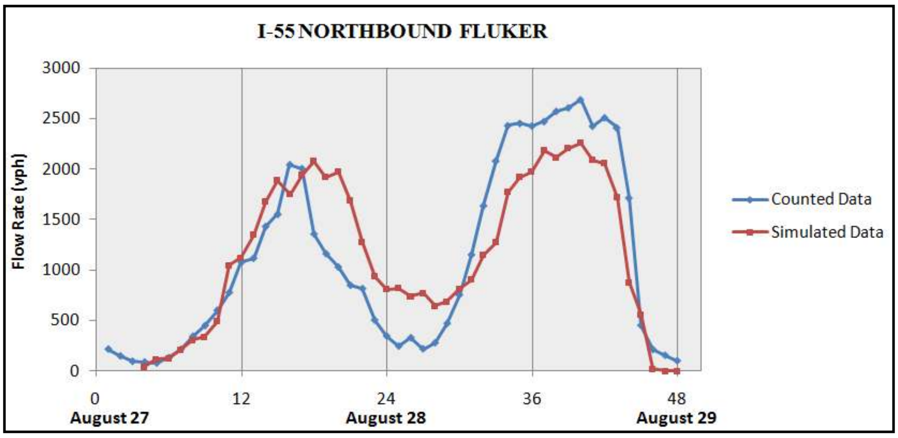
In deciding the first level destination for each agent at the initial phase of the model simulation (i.e. east, west, north, US-61, or LA-1), each agent was assumed to go to its nearest highway access. Hence, for each final evacuation direction, the travel distances of all agents to their nearest highway accesses that can ultimately lead them to the desired final evacuation direction were calculated and sorted. The lowest value of the travel distances was set as the agent's final evacuation direction. The following figure 3.8a to 3.8e show the computed initial positions of all the agents who are heading toward east, west, north, US-61, and LA-1 final destinations, respectively.



(a) Westbound I-10 ((LaPlace, Louisiana)



(b) Eastbound I-10 (Slidell, Louisiana)



(c) Northbound I-55 (Fluker, Louisiana)

Figure 3.7. Traffic count data and simulated data during Hurricane Katrina

(a) 3068 agents heading toward east

(b) 5330 agents heading toward west

(c) 3946 agents heading toward north

(d) 3219 agents heading toward US61

(e) 2181 agents heading toward LA1

Figure 3.8. The initial locations of the agents heading toward each evacuation direction

3.4.4 Routing Sub-Model

It was assumed that the evacuees know the optimal routes all the time, in terms of travel time path to reach the nearest highway access nodes. This means that when an agent arrives at a node (i.e., intersection), he/she will evaluate all the possible routes that can lead to the desired highway accesses. After assessing these available routes, the agent will finally choose the optimal path and drive accordingly. In this study, the routing sub-model, which is also called the shortest path model, was used to solve this problem of how to choose the optimal path when arriving at a node (see also Qin, 2009).

The main purpose of this optimal path model is to find the optimal path from any origin node to all other nodes. The basic idea of this model is to build a matrix, and the shortest distance between any two nodes in the road network is stored in this matrix. An agent does not consider the next link to drive onto until it arrives at a node (i.e. intersection). For example, when an agent arrives at any given node, the travel times of all its adjacent nodes to their desired nearest highway entrances are compared. Then the link connected to the node with minimum travel time to the aimed highway entrances is chosen and the agent drives onto this road segment at a current time step. The minimum travel time matrix is updated based on the real time traffic situation at each time step.

The most famous algorithm used to find the shortest path is credited to Dijkstra (1959). It works by visiting nodes in the graph starting with a given node. It then repeatedly examines the closest not-yet-examined nodes, adding this node to the set of nodes already examined. It expands outward from the starting node until it reaches all the other nodes. This above process is repeated for every node to find their nearest distance (i.e., travel time) to other nodes. In this study, when a node searches its shortest travel time to other nodes, it does not need to retrieve every other node. The process stops when the currently examined node is one of the desired, in terms of final evacuation direction and highway access, because this means the nearest distance from this node to highway entrances is already found. The final result of the shortest travel time of all the nodes to all three final destinations (e.g. east, west, and north) is listed as an origin-destination (O-D) matrix, which is updated in every simulation time step and serves as input to VISSIM^{TM}.

3.5 Vehicle-Based Microsimulation Model

Although vehicle-based microsimulation models are often preferred for more detailed, accurate simulation, two shortcomings of microscopic simulation models sometimes hinder the use of these models: the relatively long simulation running time and the complexity of road network preparation. One major reason of the long simulation running time of microsimulation models is caused by the complex road network. In the road network preparation phase, every lane of the links is configured the same as a real road situation, which is a heavy burden when simulating a large and complex road network. The calibration phase of these models also consumes a large amount of time because of the strict requirement of the road network construction in the simulation environment. By using the proposed integrated two-level approach, model running time is expected to be reduced substantially.

3.5.1 Simulation Environment

In this study, the highway part of regional evacuation simulation used VISSIM™ 4.30, which is one of the most widely-used vehicle-based microsimulation models in transportation analysis. Most of the default values of the parameters were used in this study, such as car-following, lane-changing rules, and intersection regulations. At each time interval, the O-D matrices for the highway access points (called parting lots in VISSIM™) are automatically input into the VISSIM™ simulation model. Only three destination parking lots (each for east, west, and north evacuation direction) were used for this study.

3.5.2 Dynamic Assignment

In the traditional static way of modeling a microsimulation model, the simulated vehicles follow routes through the network that were defined manually by the user, i.e., the drivers in the simulation have no choice which way to go from their origin to their destination. In this model, drivers are able to dynamically choose a better route in terms of travel time. To fulfil this purpose, VISSIM™ utilized an iterated simulation in the Dynamic Assignment procedure, which is adopted by this study. This means that a modelled network is simulated not only once but repeatedly, and the drivers choose their routes through the network based on the travel cost they have experienced during the preceding simulations. The iteration continues until a stable condition is reached (PTV, 2007).

When using Dynamic Assignment, travel demand is specified in the form of an O-D matrix (PTV, 2007). Such an O-D matrix contains the number of trips for every pair of highway access points for a given time interval (60 minutes in this study). The O-D matrices used as input data for dynamic assignment in VISSIM™ were obtained from the output of the census block centroid-based microsimulation model. This output-as-input mechanism was used to couple the census block centroid-based microsimulation model with the vehicle-based microsimulation model.

3.5.3 Destination Choice

Depending on the strength of an approaching hurricane, various destination options exist for evacuating vehicles leaving New Orleans. In this study, there are three final destinations (i.e. east, west, and north) for the interstate highway road network simulation. Because the final result of this simulation model is the total evacuation time, which was recorded as the time between the first vehicle starting to evacuate and the last vehicle reaching its evacuation destination, we set the locations that have traffic counters for each evacuation destination as the end link (i.e., final destinations: LaPlace for I-10 west, Slidell for I-10 east, and Fluker for 1-55 north) (Figure 3.3a).

3.6 Integrated Agent-based Microsimulation Model Calibration and Validation

After the development of all the sub-models for the census block centroid-based model and the vehicle-based model, the integrated microsimulation model is built. The first important question is whether the simulation results obtained from the developed model are credible and can produce similar results in the field. Therefore, to ensure that the model produces reasonable results, both parameter calibration and field validation are considered (Jamei, 1984):

3.6.1 Parameter Calibration

Five parameters need to be calibrated in the census block centroid-based microsimulation model. The parameters that should be adjusted in this integrated agent-based microscopic model are *a* and *b* in equation 2, which determine the travel speed for each link in the census block centroid agent-based model, and *c*, *d*, and *z* in equation 6, which determine the loading rate. The data used to calibrate the model is the traffic count data on westbound I-10 during Hurricane Katrina at LaPlace from 27 August at 12:00am to 29 August at 12:00am, shown in Figure 3.7a.

The simulation model was tested using the following ranges: *a* from 0 to 1000, *b* from 1 to 8, *c* from 0.5 to 1.5, *d* from 0.1 to 1, and *z* from 0.001 to 0.04. By choosing many alternative parameter combinations, a set of values (a=15, b=2, c=1, d=0.65 and z=0.002) that can fit the simulated traffic volume and real traffic count volume relatively well. Figure 7a compares the simulated traffic pattern (average value for 10 times simulations) with the real traffic count data.

As is seen in Figure 3.7a, the shape of the simulated data curve fits the count data curve well at most times. The major difference between these two curves is that one of the depressions for the real count data curve caused by the contraflow implementation at Aug 27th 16:00pm that the simulated curve did not have. The reason for the difference could be that the contraflow was implemented a few hours later after the evacuation order was issued. However, in our model, due to the difficulty of dynamically changing the road network configuration in VISSIM™, the contraflow was implemented at the beginning of the evacuation order in the vehicle-based microsimulation model simulation.

3.6.2 Field Validation

Field validation is an important process of determining the extent to which the model's fundamental rules and relationships are able to portray actual traffic behavior as specified by underlying theories and field data. Since this agent-based microsimulation is a stochastic process in which every computer run represents a single observation, a complete experiment consisting of ten computer runs and the average results were used in the following study. The data used to validate the integrated agent-based model were also from the Hurricane Katrina traffic count data in New Orleans from 27 August 12:00am to 29 August 12:00am at two locations: Fluker on I-55 northbound for north evacuation and Slidell (near rest area) on I-10 eastbound for east evacuation. From Figures 7b and 7c it can be visually determined that the simulated data curve fit the count data curve very well at most places. This means that this integrated model can simulate the regional evacuation traffic with acceptable results.

3.7 Results and Analysis

Every simulation result (i.e. evacuation time) used is the average value from 10 time runs. The 95% confidence intervals for the simulation results were then calculated (Chen, 2006).

The running time for each simulation is closely related to the performance of the simulation environment and the congestion level in running the simulation model in a computer with the following specifications: CPU (Intel Core 2 Duo 2.60 GHz), RAM (3.00 GB), and Windows VISTA operation system. The simulation model running times range from 13 to 15 hours at most times.

The primary result that we are looking for in this study is the overall evacuation time needed to evacuate all the endangered people, and this value can be obtained in the vehicle-based microsimulation model. To fulfil this task, VISSIM™ recorded the start time of the running model as the initial time, and assumed that the evacuation ending time is the time when the last vehicle passed any of the three traffic record locations (I-10 LaPlace, I-10 Slidell, and Fluker on I-55). After simulating the model for about 10 times, it was concluded that most of the evacuation ending time happened at the Fluker on I-55, which may due to the fact that the Fluker recording location is farthest from New Orleans.

The results show that it takes an average of about 46.4 hours to evacuate the whole New Orleans traffic under the simultaneous evacuation strategy (i.e., every evacuee has the same priority, and can participate to evacuate any time he/she likes). The evacuation times across the ten runs are very consistent. At the 95% confidence level, the range of the differences in the evacuation time is only 14 minutes. This means that under a simultaneous evacuation strategy, at least 46.4 hours are required to evacuate all residents from New Orleans metropolitan area. One scenario of traffic simulation at the 27th hour of evacuation is shown in Figures 3.3b and 3.3c.

3.8 Conclusion

This chapter describes in detail on how to build an integrated agent-based microsimulation model to simulate the mass evacuation traffic. The integrated simulation model is composed of two parts: a census block centroid-based microsimulation model developed in this study to simulate the local part of evacuation traffic, and a vehicle-based microsimulation model using existing software VISSIM™ to simulate the interstate highway part of evacuation traffic. The two models are linked through the origin-destination (O-D) matrixes. The O-D matrixes are the output from the census block centroid-based model, which are automatically linked as input to the vehicle-based model. After calibration and validation, model parameters that best simulate the real traffic counts are: a=15, b=2, c=1, d=0.65 and z=0.002. The integrated model simulation time is acceptable even on a normal personal computer, with an average of about 17-21 hours to simulate one scenario of evacuation traffic in New Orleans. Of this, about 4-6 hours were needed for running the census block centroid-based microsimulation model and about 13-15 hours were needed for running the vehicle-based microsimulation model.

There are several virtues of this integrated simulation model. First, if we use the macrosimulation model alone is used to simulate the regional evacuation traffic, the simulation results would be coarse. At the same time, it would take too much time to prepare and run a complex local road network if the vehicle-based microsimulation were used to simulate the local area evacuation. By combining the census block centroid-based microsimulation model with the vehicle-based microsimulation model, the microsimulation study's scope can be extended from local to regional, with reasonable simulation running time and accuracy. Second, the census block centroid-based microsimulation model developed in this study allows each agent to dynamically choose its travel route and highway access nodes. This improves the simulation accuracy and makes the simulated situation more realistic. Third, the user-friendly simulation interface created for this study can show dynamically the entire traffic evacuation process and help inform the decision-makers and the public. Last but not the least, this study only used the simultaneous simulation strategy in simulating the evacuation traffic, which was adopted during Hurricanes Katrina and Gustav. With the development of this integrated model, future study can be extended to explore other evacuation strategies, as well as other traffic issues in New Orleans and other urban areas.

Chapter 4 . Effects of Evacuation Strategies

4.1 Introduction

Although the mandatory evacuation of all peoples in a region may be expensive and inconvenience, it still must be implemented when people are threatened by severe disastrous events, such as an approaching Category 4 or 5 hurricane, a sudden explosion of chemical substances, an outbreak of wildfire, or other similar emergency situations. In the case of a hurricane threat, because of the complexity of land-sea interaction and hurricane landfall modeling, the track of a hurricane may deviate from the earlier prediction in the last one or two days. This has caused problems regarding mass evacuation of people in large metropolitan area. For example, both Hurricane Andrew in 1992 and Hurricane Gustav in 2008 were forecasted to hit New Orleans, mass evacuation orders were issued and people flocked through congested highways to areas such as Baton Rouge and other more inland areas. Both hurricanes ended up striking Baton Rouge more directly, making the evacuation of New Orleans seem unnecessary and wasteful. In addition to cost and potential danger during mass evacuation, a serious consequence could be that people become more skeptical and unwilling to evacuate when an evacuation order is issued next time. Every hurricane prediction model generally follows the rule that the closer in time the model predicts landfall, the better chance of a correct prediction. Therefore, to make sure that the area is truly in great danger, decision-makers would try to issue the evacuation order as late as possible with the premise that all the people can be safely evacuated. Two things could help decision-makers decide on how late an evacuation order can still be issued to successfully evacuate the entire region: 1) to obtain an accurate network clearance time needed; and 2) to decrease the overall network clearance time needed.

Previous study on regional evacuation modeling has centered mostly on the first issue of accurately estimating the time it would take to clear a specified zone of population. Very few studies have focused on the possibility of network clearance time improvement by implementing certain evacuation strategies (Chen, 206). In general, there are two ways to decrease the network clearance time: physical methods and behavior strategies. Physical methods include building new roads, implementing the new intelligent transportation systems (ITS), and others. On the other hand, behavior strategies try to improve the evacuation effectiveness by using only the currently available road network and infrastructure. Current behavior strategies consist of the implementation of contraflow and staged evacuation. The staged evacuation strategies basically divide the evacuees into several evacuation groups based on certain criteria, and designate a certain time interval for the evacuation starting time for different groups (Chen, 2006; Liu et al., 2006).

This study proposes and evaluates two new staged evacuation strategies by incorporating the concepts of spatial and social vulnerabilities (Cova and Church, 1997; Cutter et al., 2003). New Orleans, which has experienced several mass evacuations, is selected as the study area to demonstrate and evaluate the two new strategies. The integrated agent-based microsimulation model developed previously in Chapter 3 was used in the simulation.

4.2 Background

The integrated two-level agent-based microsimulation model was developed previously to simulate evacuation traffic. Detailed description of the model can be found in Chapter 3. To describe the train of thought of this study clearly, the following provides a brief description of the staged evacuation.

4.2.1 Staged Evacuation

After issuance of an evacuation order, traffic volume will surge rapidly and can cause congestion. Because a statistical assumption can be made that the aggregate distribution of originating vehicles in a neighborhood follows a Poisson distribution (Cova and Johnson, 2002), an ultimate decrease in the originating vehicle number should mitigate the traffic congestion. As such, one feasible way to solve this problem is to use the staged evacuation strategy rather than simultaneous evacuation. In the simultaneous situation, all residents in the affected area are informed to evacuate within the same time period; whereas, in a staged evacuation, residents in different zones are organized to evacuate in a sequence (Chen, 2006). Very few studies have been done on staged evacuation. Chen (2006) was among the first to experiment with staged evacuation. In Chen's study, the affected area was divided into four parallel zones, and then grouped into two groups. The starting evacuation time had a time gap among each group. Two sets of general road networks for testing the effectiveness of simultaneous and staged evacuation strategies were used, one was a simulated grid network and the other was a simulated ring road network. The simulation result showed that the staged strategies reduced the evacuation time in both grid and ring road networks. With this conclusion, Chen also investigated further on Galvestion County, TX, which has a larger real road network. A link-node based traffic analysis model was developed to estimate the network clearance time. The simulation results showed that the simultaneous strategy used an average of 16.65 hours to evacuate, while the best staged evacuation strategy used only 15.67 hours to evacuate. Although there were some reductions in evacuation clearance time, the stated evacuation strategies used by Chen were determined arbitrarily. The present study proposes that using stated strategies based on some measures of vulnerability would help decision-makers. In this paper two types of vulnerability, spatial and social, were evaluated. The details are discussed below.

4.3 Integrated Agent-Based Microsimulation Model

Despite having many advantages and applications, there are still problems in vehicle-based microsimulation modeling. First, due to the detailed nature of this type of model, preparation of input data (e.g., network coding and representation) can be very time consuming and tedious. In addition, microsimulation models are highly sensitive to errors or variation in input demand data, especially under congested conditions. Finally, due to the complicated structure of the models involved, calibration of the model is not trivial. For these reasons, vehicle-based microscopic models are usually applied to smaller networks and may suffer from boundary effect problems (Burghout et al., 2005).

To overcome the shortcomings of the vehicle-based microsimulation models, a vehicle-based microsimulation was used to simulate the interstate highway traffic flow, and a census block centroid-based microsimulation model was used to simulate the local traffic for regional evacuation. For the simulation of the highway traffic, a piece of existing software, VISSIM™, was utilized. Because the interstate highway road network configuration is relatively simple, the times needed to prepare input data and model runs are not expected to be long. Also, because most of the evacuation travel time would be spent on interstate highway and the vehicle-based microsimulation can simulate the traffic flow quite accurately, the overall simulation result should be reliable.

Compared with the interstate highway, the local road network configuration is much more complex. In our census block centroid-based microsimulation model, each census block centroid is treated as a dynamic agent, with the number of vehicles of a given census block as its weight. These agents move and interact with each other during simulation. The destinations for them are the highway access nodes, and the number of vehicles arriving at their destination for each interstate highway access during every time interval (e.g. one hour) is recorded. By using this local traffic simulation output, a set of origin-destination (OD) matrices is created as input to the vehicle-based microsimulation model for interstate highway traffic simulation.

This output-as-input mechanism effectively integrates the two agent-based models together to simulate the traffic flow for regional disaster evacuation.

Using integrated agent-based microsimulation model, the three regional evacuation strategies were simulated and their effectiveness evaluated. The three evacuation strategies included: 1) simultaneous evacuation strategy; 2) staged evacuation strategy based on spatial vulnerability; 3) staged evacuation strategy based on social vulnerability.

Since the simultaneous evacuation strategy was adopted during Hurricane Katrina, the total network clearance time used in that simulation, which was 46.5 hours for the New Orleans metropolitan area (from 08/26/2005 4:00 am to 08/29/2005 2:30 am), can be used to compare with the simulation results of the two-staged strategies. The following describes how spatial and social vulnerabilities were defined and how the evacuation groups were classified for staged evacuations.

4.4 Staged Evacuation Strategy I – Spatial Vulnerability

One of the most straightforward criteria (i.e. vulnerability) may be the spatial vulnerability. The idea of this criterion is that people in high spatial vulnerability areas might spend more time on evacuation traffic than people in low spatial vulnerability areas, so it might be prudent for them to evacuate first.

4.4.1 Spatial Vulnerability

To identify the spatial vulnerability for every resident, this study basically adopted Cova and Church (1997)'s method, but also made some changes in some aspects to improve the model accuracy and reliability.

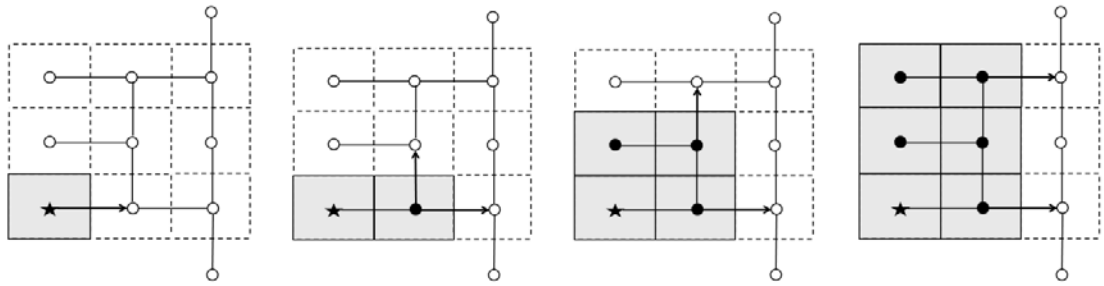
The spatial vulnerability for a node (i.e., E_i) is defined as equation 7, and every node in the road network should be calculated respectively to get its own spatial vulnerability.

$$E_i = \sum_{i=1}^{i=n} P_i \Big/ \sum_{j=1}^{j=m} C_j \qquad (7)$$

where n is the number of nodes in current cluster, P_i is the number of vehicles represented by the ith node, m is the total number of exit links in the cluster, and C_j is the link capacity of the jth exit link. Exit links are the links that directly connect one node in the current cluster with another node outside the cluster. Any node in the cluster must be connected with one or more other nodes that are also in current cluster, and the cluster must include the initial node (i.e., current root node).

To calculate the spatial vulnerability for a node, considered a given node (called root node), the method is to explore the road network for several steps and to find a series of directly adjacent (by using road links) node clusters. At each step, one node that is directly connected to the current cluster is selected and enclosed to form a new contiguous cluster to be used in the next step. Also, the spatial vulnerability for each cluster during this exploratory process is calculated by using equation 7 at each step, and the cluster with the maximum spatial vulnerability value among these clusters is called the critical cluster (Cova and Church, 1997). This maximum spatial vulnerability is then considered as the final spatial vulnerability for this given node.

Figure 4.1 is an example showing how to explore the road network to find out the critical cluster for a given node that has the maximum spatial vulnerability value. This road network consists of 11 nodes and 11 road links. We assume that every node represents 500 vehicles, and each link has the same capacity (e.g. 1 vehicle/second). We would explore five steps in this example for the root node. The root node is represented by a star in Figure 4.1, and the nodes in current cluster are represented by solid circles, while the nodes outside the cluster are represented by hollow circles. The road link between two nodes is represented by solid line, and the link that directly connects one node in the current cluster to another node outside the cluster (i.e. exit link) is represented by a solid arrow line.



(a) The initial phase (b) The first step (c) The third step (d) The fifth step

Figure 4.1. An example showing the process of exploring the node cluster from the root node (source: Cova and Church, 1997)

At the initial phase in Figure 4.1a, the node cluster only consists of the root node, and the total exit capacity is 1 since only one link connects the node in the cluster to a node outside the cluster. So the spatial vulnerability for the root node is 500. In the next step (Figure 4.1b), one node from the directly connected nodes is enclosed and forms a cluster. In this cluster, it includes 1000 vehicles and the exit capacity is 2, so the spatial vulnerability is 500. In the third step (Figure 4.1c), the cluster includes 4 nodes (i.e. 2000 vehicles) and the exit capacity is 2, so the spatial vulnerability is 1000. In the last step (Figure 4.1d), the cluster includes 6 nodes (i.e. 3000 vehicles) and the exit capacity is 2, so the spatial vulnerability is 1500. By comparing these spatial evacuation vulnerabilities of all the clusters in each step, the maximum spatial vulnerability of this root node occurs at the six-node situation in this example, and the final spatial vulnerability of this root node is 1500.

To calculate the spatial vulnerability for each node, three major issues should be clarified first:

1) How to calculate the number of vehicles represented by each node:

In the common spatial data model for transportation road network in GIS, the polyline features represent road segments and nodes (i.e. junctions) represent the street intersections. Also, the finest existing census data are at the census block level, and each census block is represented by its centroid in this study. To determine the number of evacuation vehicles represented by each node, Cova and Church (1997) used Thiessen polygons based on Euclidean distance to aggregate population for each street intersection. However, even though the idea of Thiessen polygon method is straightforward, it is not accurate especially in some extreme cases. In light of this drawback, this study adopts a road network distance method. The basic idea of this modified aggregation method is to find the desired node with the least travel time (no traffic considered) for each census block centroid first, and then add up the number of vehicles (represented by centroids attribute) with the same initial approaching node together as the attribute for each given node.

2) How to determine the maximum number of nodes in a cluster during the cluster exploring process:

To obtain the spatial vulnerability for each node, equation 7 should be used. This spatial vulnerability calculation is an exploratory process to form a series of clusters for each node around its local neighborhood. The maximum number of nodes when exploring the road network to form a cluster should be specified (e.g., the above example in Figure 4.1 uses six as the maximum number of nodes in a cluster). Since the maximum spatial vulnerability may be occurred at any of these node clusters, this exploratory process cannot be stopped until all the alternative clusters are found. In Cova and Church's (1997) study, three maximum number of nodes in one exploring cluster(i.e. 10, 25, and 50) were used respectively to limit the process of finding the maximum spatial vulnerability value, and the average result was used as the final spatial vulnerability value for one given node. In this study, the middle number 25 was adopted as the maximum number of nodes in an exploring cluster to simplify the exploring process.

3) How to define the capacity of the exit choice set:

In Cova and Church's (1997) study, the number of lanes was used as capacity for every road link, which has very coarse accuracy. To improve the accuracy, the real road capacity data obtained from New Orleans Regional Planning Council was adopted to calculate the capacity of exit choice set.

4.4.2 The Critical Cluster Model

The critical cluster problem involves finding the most difficult evacuation starting scenario associated with a pre-specified root node (Cova and Church, 1997). For any given node, to specify the maximum number of nodes in the cluster exploring process, there must exist at least one cluster of nodes that can maximize the ratio of number of vehicles to exit capacities.

The way to locate a critical cluster for a root node is by using the heuristic growing method. Beginning with one given node, the heuristic method iteratively adds one of currently adjacent nodes to the existing contiguous cluster (Cova and Church, 1997). Three concepts/parameters should be specified before deciding which node should be added at each iteration: 1) gain in objective if node *i* is selected; 2) *alpha*; and 3) *starts*.

First, the gain in objective if node *i* is selected can be formulated as equation 8:

$$g_i = Ei_{(k+1)} / E_{(k)} \qquad (8)$$

where $Ei_{(k+1)}$ is the spatial vulnerability with node *i* selected at step $k+1$, and $E_{(k)}$ is spatial vulnerability at the k^{th} iteration. The *i* can be any node ID adjacent to the current contiguous cluster. To choose the next node to be added into current cluster at any time step and avoid local optima, a "semi-greedy" approach that can greatly improve the solution quality was used by Cova and Church (1997). In their semi-greedy approach, the *alpha* and *starts* parameters should be specified first. For all the adjacent nodes in any given cluster, the nodes that have the g_i value obtained from equation 8 greater than *alpha* percent of the best g_i value have the equal opportunity to be chosen at this iteration. To fulfill this equal chosen opportunity aim, a random selection is made from these candidates at each step (Cova and Church, 1997). This selection process should be repeated for *starts* times, and then the best solution should be selected from them.

In this study, all census blocks were finally classified into two evacuation groups (i.e. high spatial vulnerability group and low spatial vulnerability group). Yet for better analysis and visualization, the nodes were first classified into four classes (i.e. least vulnerable class, less vulnerable class, vulnerable class, and the most vulnerable class), and the desired classification accuracy was set at 95 percent for this study. Based on Cova and Church's (1997) study, to reach this 95 percent of classification accuracy, an *alpha* value of 0.95 and a *starts* value of 16 were used.

In the process of exploring a critical cluster for a given node in Cova and Church's (1997) study, a global exit may not be selected as a component node of any cluster. This setting might be suitable for the exit nodes *per se*, for which the spatial vulnerability value can be set to zero. However, whether reaching an exit or not should be taken into consideration when exploring a critical cluster. We cannot simply take the exit nodes (i.e. interstate highway accesses) out from the road network and then calculate the spatial vulnerability for the rest of the nodes. The theoretical basis for this reasoning is rather straightforward since the residents living near the exits can surely reach the exits easier than the others. Thus they should have a smaller spatial-vulnerability value. To add this consideration into the critical cluster exploring method in this study, the semi-greedy approach was slightly modified. That is, at any step, if any node adjacent to the current contiguous cluster is an exit node, the critical cluster exploring process should be terminated even if the evacuation size limit has not been reached. Furthermore, there are five final evacuation directions (i.e. LA-1, US-61, I-10 east, I-10 west and I-55 north) for the New Orleans Metropolitan area, but some exit nodes cannot access all these five evacuation directions. In light of this access limitations, the spatial vulnerability may be different for a single node for different evacuation directions. Hence, each node should have five evacuation vulnerabilities for every evacuation direction.

After specifying all these required settings and corrections for the critical cluster exploring model, the spatial vulnerability can be obtained for each node respectively, and we can then assign the spatial vulnerability of each node to every corresponding census block centroid. Finally, all the census block centroids were classified into two classes, low spatial vulnerability and high spatial vulnerability, and each class has about the same number of evacuation vehicles. The road network used for this calculation is the major roads in New Orleans obtained from Google Maps™ (Figure 3.6).

4.4.3 Grouping Based on Spatial Vulnerability

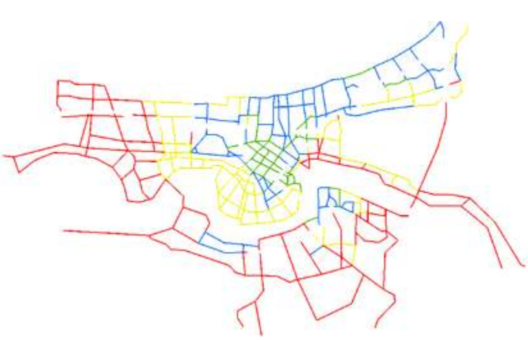
Since there are totally five final evacuation directions, the spatial vulnerability should be different for each node and each direction. So, these evacuation vulnerabilities were calculated for each direction individually. Also, as there are too many census blocks (17,744 in New Orleans Metropolitan area) and they are hard to distinguish by officials and also by residents, census tract (334 in New Orleans Metropolitan Area) was used as the final administrative unit to issue the evacuation order in this study. This means, after the spatial vulnerability was obtained for each census block, the average spatial vulnerability of all the census blocks that fall into the same census tract was set as the spatial vulnerability of each given census tract. And then, based on the evacuation vulnerabilities of these census tracts, half of the census tracts with relatively high evacuation were classified into one evacuation group, while the rest census tracts were put into the other evacuation group.

To summarize this spatial vulnerability based grouping method involves five major steps: 1) calculate the weight (number of vehicles) for each node, 2) for every evacuation direction, calculate the spatial vulnerability for each node individually, 3) for every evacuation direction, compute the spatial vulnerability for each census tract, 4) classify all the census tracts into two evacuation groups (i.e., low spatial vulnerability group and high spatial vulnerability group), and 5) assign the spatial vulnerability of each census tract to those census block centroids that fall inside its area.

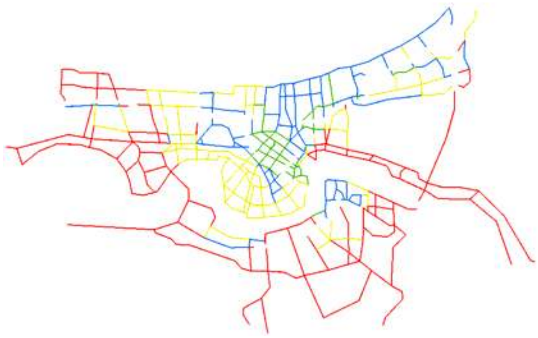
When the second step above is finished, the spatial vulnerability for each node is determined and mapped over the entire study area. To better visualize the spatial vulnerability over the entire road network, the spatial vulnerability for each road link was computed. The spatial vulnerability of a link is defined to be the worst-case vulnerability level of its two end nodes. The vulnerabilities of the links were classified into four levels by using the *natural break* method into least vulnerable, less vulnerable, vulnerable, and most vulnerable. Each level has the same number of links. Figure 4.2 shows the different spatial vulnerability levels of the entire road links for each evacuation direction.

Based on the spatial vulnerability for each census block, the spatial vulnerability of each census tract was calculated by using the average spatial vulnerabilities of all the census block centroids fall inside this given census tract. All these census tracts were then classified into four levels by using the *quantile* method to make sure that each level has the same number of census tracts: least vulnerable, less vulnerable, vulnerable, and most vulnerable. In fact, the last two-level census tracts were combined into the first group to receive the early evacuation order, and the late evacuation order would be issued to the first two level census tracts after a given time interval. Figure 4.3 shows the spatial vulnerability levels of the entire census tracts for each evacuation direction.

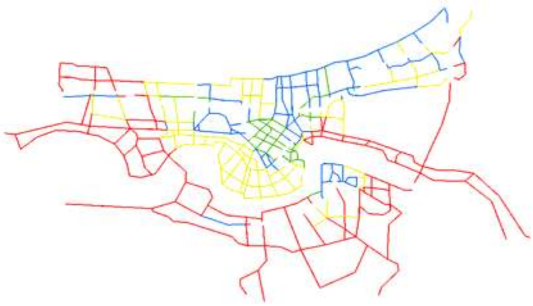
The purpose of this study is to assess the effectiveness in terms of network clearance time of some staged evacuation strategies proposed in this study. Also, based on different spatial vulnerability for each census tract calculated in this section, all the census blocks in the study area can be classified into two groups, which is a precondition to simulate the staged evacuation strategy. With a different evacuation order time issued to these two groups (the high spatial vulnerability evacuees would receive an early evacuation order, while the low spatial vulnerability evacuees would receive a late evacuation order), the spatial vulnerability-based staged evacuation strategy can be simulated by using the integrated microsimulation model developed in Chapter 3.



(a) East evacuation direction



(b) West evacuation direction



(c) North evacuation direction

(d) LA1 evacuation direction

(e) US61 evacuation direction

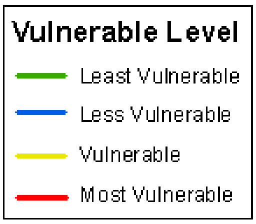
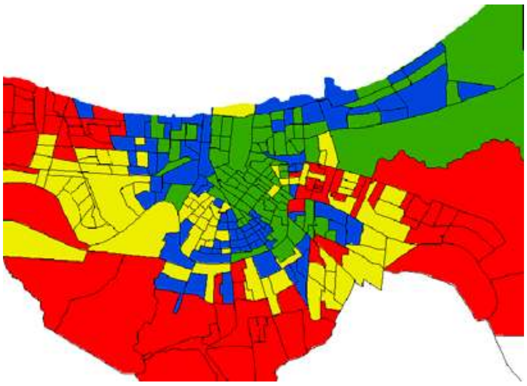
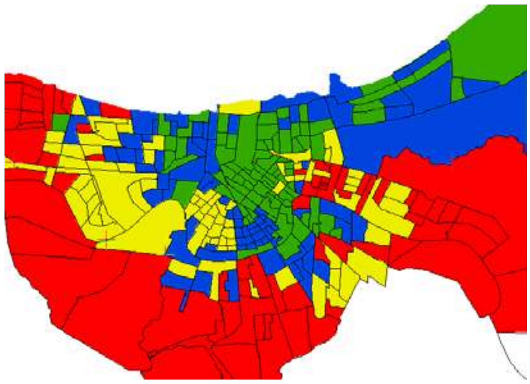


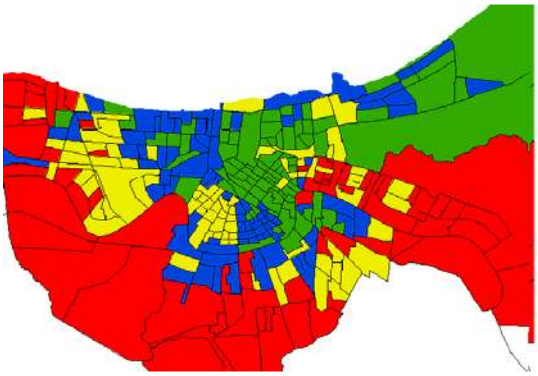
Figure 4.2. The spatial vulnerability of all the links for each evacuation direction



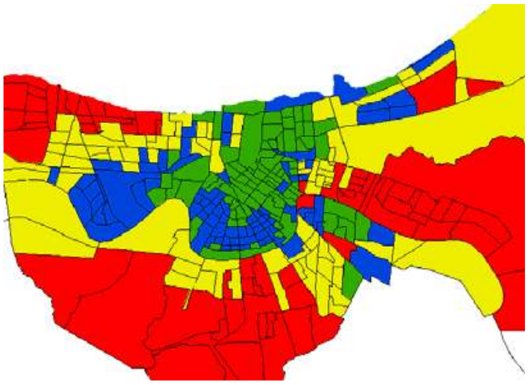
(a) I-10 east evacuation direction



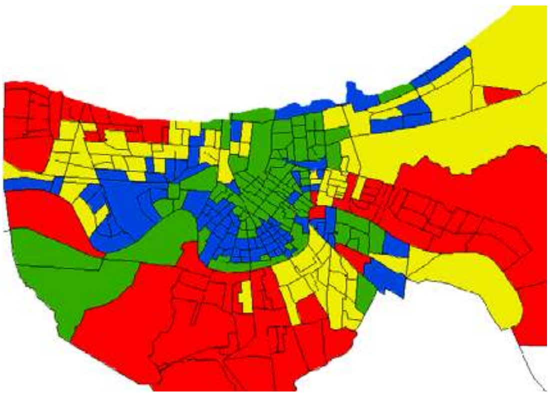
(b) I-10 west evacuation direction



(c) I-55 north evacuation direction



(d) LA1 evacuation direction



(e) US61 evacuation direction

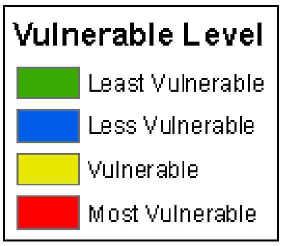


Figure 4.3. The spatial vulnerability of all the census tracts for each evacuation direction

4.4.4 Staged Strategy I Simulation

The simulation model is ready to be executed after specifying two parameters. First, for staged evacuation, one parameter needs to be set is the *interval time* between the two evacuation groups, meaning that vehicles in the second group start to evacuate a certain amount of time after vehicles in the first group have started to evacuate. Since there are no empirical data upon which the time interval for a staged evacuation can be determined, Chen (2006) used a 30-minute interval between the four evacuation zones in her research. However, we believe that the optimal time interval should be different for different study areas and different evacuation strategies. So, to obtain a more accurate time interval, a set of alternative values was experimented, ranging from 0.5 hour to 8 hours with a 30-minute interval between each alternative interval.

The other issue/parameter needs to be set is the half-loading time for the traffic demand sub-model in the census block centroid-based microsimulation model. For the first evacuating group, it is assumed that it would use the same half-loading time as the simultaneous evacuation strategy. But the late evacuation departure group would feel more anxious than the first group, and thus are more likely to begin to evacuate early. To take this behavior change into consideration, it is assumed that the half-loading time for the second evacuating group is the value of half-loading time for the first evacuating group minus half of the time interval between these two groups.

After all these parameters were specified, the integrated microsimulation model developed in Chapter 3 was used to simulate the dynamic traffic flow using this spatial vulnerability-based staged evacuation. Since the integrated agent-based microsimulation is a stochastic process in which every computer run represents a single observation, a complete experiment consisted of ten computer runs and the average results are used in this study.

The simulation running time for each run is closely related to the performance of the simulation environment and the congestion level in the simulation. By running the simulation model in a computer with the following specification: CPU (Intel Core 2 Duo 2.60 GHz), RAM (3.00 GB), and Windows VISTA operation system, the simulation model running time ranged from 11 to 14 hours at most times.

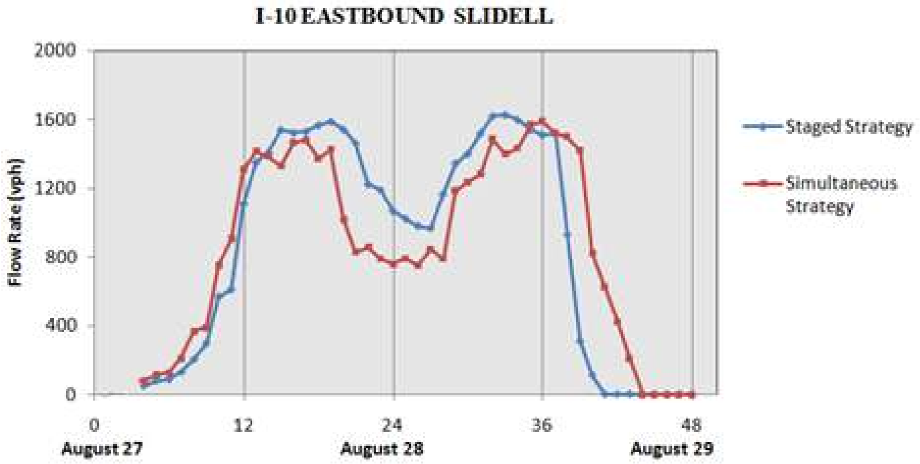
The primary result is the overall network clearance time needed to evacuate all the endangered people, and this value can be obtained in the vehicle-based microsimulation model. To fulfill this task, let VISSIM record the start time of model running as the initial time, and the evacuation ending time is the time when the last vehicle passes any one of the three traffic record locations (I-10 LaPlace, I-10 Slidell, and Fluker on I-55). After several simulations, most of the evacuation ending time ended at the Fluker on I-55 location. This happens because the Fluker recording location is the farthest away from New Orleans among the three recording locations. Table 4.1 shows the average network clearance time used with each time-interval between the two evacuation groups.

From the results in Table 4.1, the minimum network clearance time was about 42.8 hours for this staged evacuation strategy, with a 3.5 hours time interval between each evacuation group. Since the network clearance was about 46.4 hours for simultaneous evacuation strategy, this spatial vulnerability-based staged evacuation strategy decreased the overall network clearance time by about 3.6 hours.

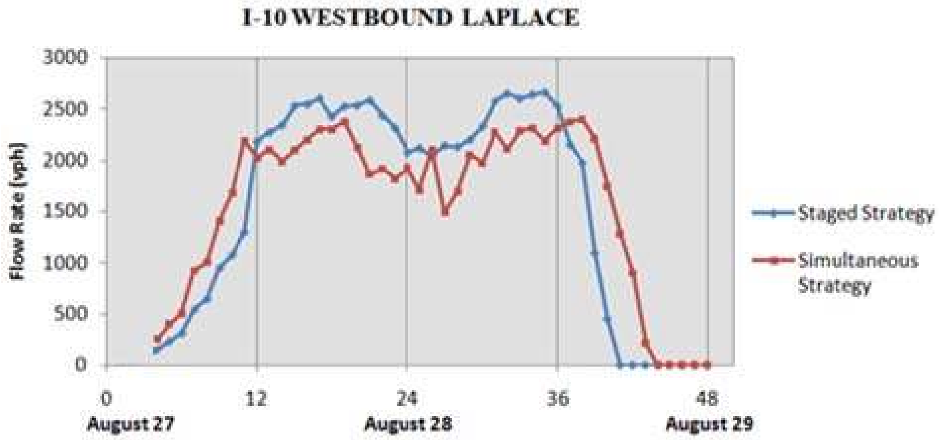
The simulated data curves for simultaneous evacuation strategy and spatial vulnerability-based staged evacuation strategy were compared in Figure 4.4a (for I-10 east traffic), Figure 4.4b (for I-10 west traffic), and Figure 4.4c (for I-55 north traffic). In each evacuation direction, this staged evacuation strategy can always save more than three hours network clearance time over the simultaneous evacuation strategy for New Orleans evacuation.

Table 4.1. The average network clearance time (hours) for different time-interval

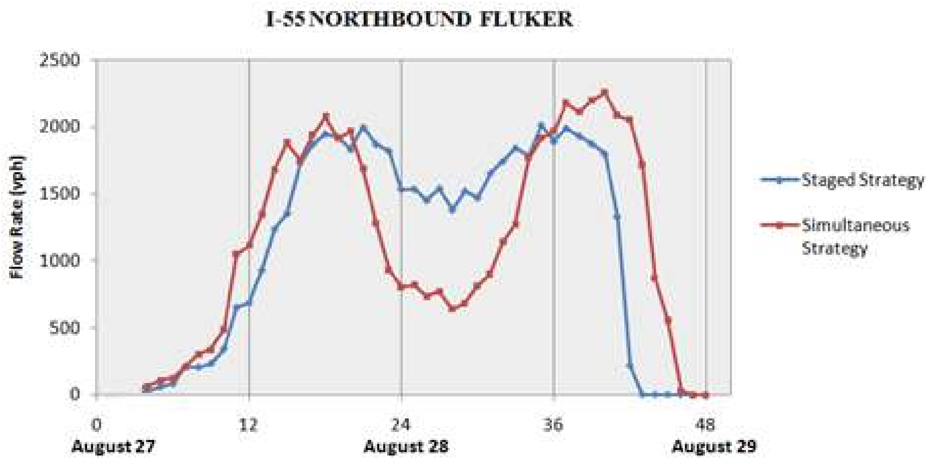
Interval-time	Network clearance time	Interval-time	Network clearance time
0.5	46.2	4.5	43.3
1	45.8	5	43.2
1.5	45.1	5.5	44.1
2	44.6	6	45.0
2.5	44.2	6.5	45.3
3	43.5	7	45.8
3.5	**42.8**	7.5	46.4
4	43.1	8	46.6



(a) Eastbound I-10 during Hurricane Katrina (Slidell, Louisiana)



(b) Westbound I-10 during Hurricane Katrina (LaPlace, Louisiana)



(c) Northbound I-55 during Hurricane Katrina (Fluker, Louisiana)

Figure 4.4. Simulated data for both staged evacuation strategy and simultaneous evacuation strategy

The evacuation times across the ten runs are very consistent. At the 95% confidence level, the range of the differences in the evacuation time was only 16 minutes.

4.5 Staged Evacuation Strategy II – Social Vulnerability

Different from the first staged evacuation strategy, social vulnerability was used to classify all the evacuees into two evacuation groups in this second staged evacuation strategy. The rationale for this staged strategy is that people with high social vulnerability are the most evacuation-endangered people. They usually do not have enough vehicles available to evacuate, and sometimes are too old or too young to drive, so they may need more time to prepare to evacuate. During Hurricane Katrina, over 10,000 people did not evacuate from New Orleans because of a variety of reasons; most of them were considered high social vulnerability residents. Given more evacuation time, they may change their mind to participate in evacuation or find an available vehicle to evacuate. Therefore, with this consideration, it is reasonable to separate the residents into two evacuation groups according to their social vulnerability, and each group has the same number of census tracts. The residents living in high social vulnerability areas would be asked to evacuate earlier than the residents with low social vulnerability.

To determine the social vulnerability of each census block group, the method of Cutter et al. (2003) was adopted with some modification (see also Qin, 2009). Socioeconomic data were collected for all the 925 census block groups in the study area. 20 independent variables were finally selected and used in the statistical analysis Table 4.2. These variables were selected based on the literature on social vulnerability (Cutter et al., 2003). Every one of these variables needs to be calculated to get its percentage value.

The primary statistical procedure used to reduce the data was factor analysis, specifically, principal components analysis, which is described in detail in the next section.

4.5.1 Factor Analysis

Because many obtained social-economic variables are inter-correlated, it is improper to integrate them together directly to obtain the social vulnerability. By utilizing factor analysis we can reduce a large number of variables to a smaller number of factors for modeling purposes, thus eliminating the inter-correlation. The technique also facilitates replication of the variables at other spatial scales, thus making data compilation more efficient (Cutter et al., 2003). A total of the first twelve factors were used, which explained over 90 percent of the variance among all the census block groups (Table 4.3).

This factor analysis was conducted in SPSS©, and one of the important output matrices is called "Component Score Coefficient Matrix". Each column of this matrix is a set factor score coefficients, which are used to calculate the factor score of each block group by using all the variable values for each of these twelve factors (Table 4.4).

After we obtained all these twelve factors, a composite social vulnerability index score was produced for each census block group, and this score is a relative measure of the overall social vulnerability. Since each of these factors interpret different potion of the information provided by the origin twenty social economic variables (e.g., first factor represents 32.301%, while the twelfth factor only represents 2.452%), each factor cannot be viewed as having an equal contribution to the census block group's overall vulnerability. So, for each factor in a given census block group, we multiplied its value with the percentage of variance of the initial eigenvalue, and finally added all these twelve multiplied values together to produce the overall social vulnerability. In this calculation process, all factors with positive values indicated higher levels of vulnerability; negative values decreased or lessened the overall vulnerability. The results showed that lowest value in all these census block groups was -1.2141, and the highest social vulnerability was 29.4907. However, just as for staged evacuation strategy I, census tract

Table 4.2. Major social vulnerability indicators used in this study (units: Percentage)

Social vulnerability indicators
Foreign born (born 1990 — March 2000)
No high school diploma (25 years of age or older)
Speak no English at home
Under 5 years old
65 years of age or older
Female
Female headed households
Unmarried (males and females)
Minority ethnicity
Renter occupied housing units
Housing units that are mobile homes
Housing units that are boats, vans, or recreational vehicles
Housing unit built before 1940
Civilian unemployment
Households earning $75,000+
Living below poverty level
Disabled (5 years old +)
Employment in farming, fishing, and forestry occupations
Employment in transportation, communications, and other public utilities
Employment in services industry

Table 4.3. Total variance explained by each component

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.460	32.301	32.301	6.460	32.301	32.301
2	1.976	9.881	42.183	1.976	9.881	42.183
3	1.689	8.443	50.626	1.689	8.443	50.626
4	1.545	7.727	58.353	1.545	7.727	58.353
5	1.318	6.591	64.944	1.318	6.591	64.944
6	1.002	5.012	69.956	1.002	5.012	69.956
7	.953	4.764	74.721	.953	4.764	74.721
8	.793	3.967	78.688	.793	3.967	78.688
9	.656	3.280	81.968	.656	3.280	81.968
10	.618	3.092	85.060	.618	3.092	85.060
11	.519	2.596	87.656	.519	2.596	87.656
12	.490	2.452	90.109	.490	2.452	90.109
13	.389	1.943	92.051	.389	1.943	92.051
14	.326	1.630	93.681	.326	1.630	93.681
15	.283	1.417	95.098			
16	.275	1.376	96.474			
17	.224	1.121	97.595			
18	.193	.967	98.562			
19	.164	.818	99.380			
20	.124	.620	100.000			

Extraction Method: Principal Component Analysis.

Table 4.4. Component score coefficient matrix

	Component													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Under5Rate	.067	-.081	-.212	.185	-.281	.326	-.283	-.260	-.098	-.360	.582	.358	.008	.413
Over75Rate	-.012	.027	.522	.079	.072	-.026	.026	-.195	-.062	.045	.064	-.091	.726	.680
FemaleRate	.062	.103	.221	.329	-.210	.356	-.262	.010	-.069	.155	-.312	-.142	-.063	-.387
DisableRat	.084	-.055	.321	.155	.081	-.193	.118	-.138	.115	.103	.486	.432	-.783	-.653
UnemployRate	.103	-.017	-.121	.017	-.040	.050	.011	.013	.365	.841	.474	-.675	.068	.104
FemaleHeadedRate	.130	.122	.086	-.009	.010	.095	-.047	-.035	-.234	-.201	-.242	-.381	-.340	.240
RentPercen	.109	.213	-.071	-.026	.120	.025	.013	-.019	-.334	-.298	.380	-.351	.365	-.423
MoreThan75000Per	-.105	.126	.058	.042	-.148	.361	-.260	.220	.212	.294	-.121	.303	.093	-.205
ServiceIndustryRate	.124	-.012	-.089	.005	-.030	-.082	.014	-.063	.170	.135	-.521	.431	.687	-.550
FamerRate	-.008	-.183	-.016	.259	.417	.021	-.334	.215	.574	-.478	-.019	-.367	.117	-.213
TransportationRate	.020	-.171	.057	.217	-.329	-.162	.276	.814	-.186	-.133	.196	-.065	.229	.057
NoEnglishRate	-.048	.252	-.160	.377	.130	-.135	.120	.057	.151	.136	-.192	.173	-.393	.815
UnMarriedRate	.128	.169	.055	-.003	.101	.049	.010	.197	-.140	-.111	-.275	-.104	-.301	.200
MinorityRate	.126	-.062	-.075	-.044	-.154	-.066	.087	.063	.169	-.038	-.470	.002	-.300	.030
ForeignBornRate	-.041	.296	-.159	.332	.055	-.177	.238	-.130	-.110	.009	.140	.049	.396	-.493
PovertyRate	.137	-.014	-.088	-.029	.054	.022	-.035	.006	.077	.053	.016	.188	.241	.314
NoHighSchool	.121	-.162	.012	.126	.087	-.130	.072	-.141	.146	.072	-.017	.419	.269	.389
MobelPercent	-.008	-.265	-.105	.155	.363	.092	-.173	.086	-.790	.456	-.135	.105	-.048	-.050
VanPercent	-.002	-.086	-.004	.014	.190	.674	.696	-.022	.128	-.089	-.017	.044	.003	-.046
HouseBefere1940Percent	.054	.241	.047	-.247	.266	.120	-.167	.530	.069	.086	.351	.537	.065	.127

Extraction Method: Principal Component Analysis.
Component Scores.

is the final administrative unit, which is going to be classified into two evacuation groups. In this case, the average social vulnerability value of all the census block groups was contained in a tract that was used to indicate the social vulnerability of this given census tract.

To classify the study area into low and high social vulnerability classes, the *quantile* method is used first to classify all the census tracts into four categories with the same number of census tracts in each group: least vulnerable, less vulnerable, vulnerable, and most vulnerable (Figure 4.5). As we can see, the most vulnerable areas were mostly located in New Orleans' downtown area, while the suburb areas were generally less socially vulnerable. In contrast to the spatial vulnerability in staged evacuation strategy I, the social vulnerability is the same for each evacuation direction of one given census tract. Then, the first two groups were combined into the first evacuation group with an early evacuation order, while the second evacuation group, combined from the last two classes, would be issued an evacuation order after a time interval are the census tracts in least vulnerable and less vulnerable classes.

4.5.2 Staged Strategy II Simulation

With the different social vulnerability for each census tract, all the census tracts (and thus census blocks) can be classified into two groups with low social vulnerability and high social vulnerability. And then, the census blocks fall inside each of these two census tract groups are consequently classified into two groups respectively. One of such group has high social vulnerability census blocks, and the other group has low social vulnerability census blocks.

With these two classified evacuation groups of all the census blocks, we are ready to simulate this social vulnerability-based staged evacuation strategy by using the integrated microsimulation model developed in Chapter 3. The group with high social vulnerability census groups would receive the evacuation order first, and then the low social vulnerability

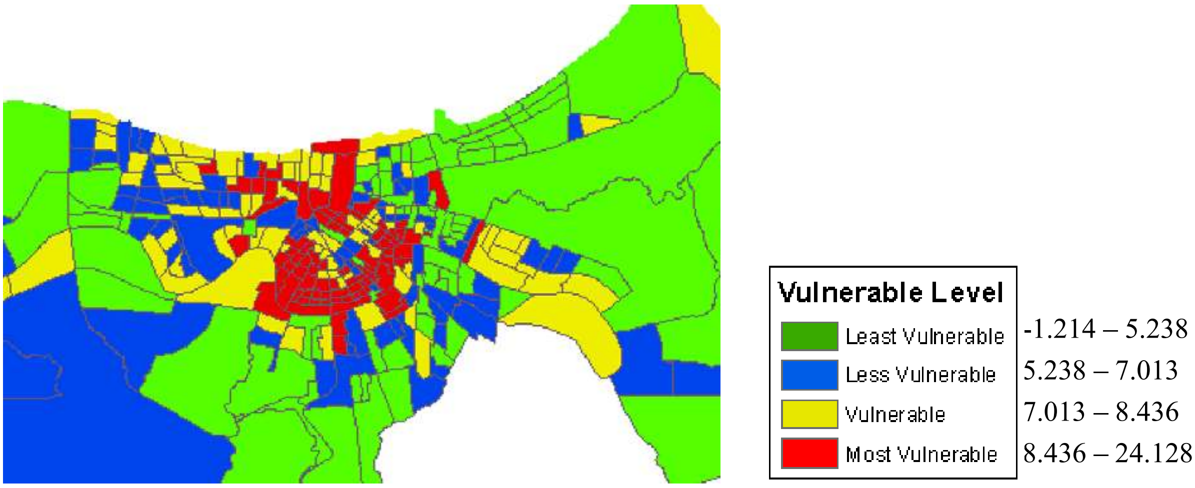


Figure 4.5. Social vulnerability of each census tract

census groups would receive an evacuation order after a time interval.

To make the simulation result comparable, the simulation environment and most of the parameter setting (i.e. the half loading time) were the same as the spatial vulnerability-based staged evacuation strategy. For the time-interval parameter between two evacuation groups, we experimented with a set of values ranging from 0.5 hour to 8 hours with a 30-minute time interval. A complete experiment consisted of ten computer runs and the average results were used in the following steps.

When we were simulating this social vulnerability-based staged evacuation strategy, VISSIM was still used to record the total network clearance time needed to evacuate all the endangered people. The same three recording locations were used (I-10 LaPlace, I-10 Slidell, and Fluker on I-55) for the traffic volume record. Table 4.5 shows the average network clearance time used for each time-interval between the two evacuation groups.

From the results in Table 4.5, the minimum network clearance time was about 44.4 hours, with the 4-hour interval time between each evacuation group. Since the network clearance was about 46.4 hours for the simultaneous evacuation strategy, this social vulnerability-based staged evacuation strategy decreases the overall network clearance time for about 2 hours. This is a significant improvement, but by comparing with the 42.8 hours of the network clearance time for staged evacuation strategy I, the effectiveness of this strategy is still not good enough. However, the network clearance time should not be the only issue considered by the decision-makers even though it is really important. With the social vulnerability-based staged evacuation strategy implemented, the potential improvement (e.g. well-ordered evacuation and high participation rate) to the high social vulnerability neighborhood would be invaluable. This makes the study of this staged evacuation strategy very useful.

Table 4.5. The average network clearance time (hours) for different time-interval

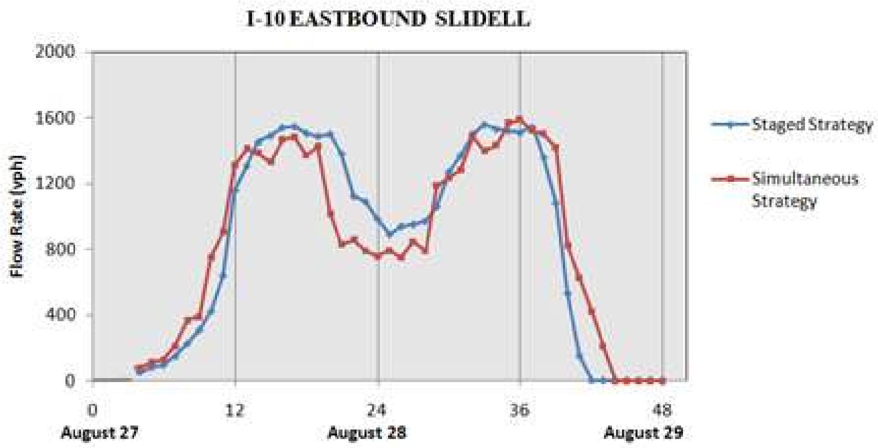
Interval-time	Network clearance time	Interval-time	Network clearance time
0.5	46.4	4.5	44.8
1	46.2	5	45.0
1.5	46.1	5.5	45.4
2	45.6	6	45.8
2.5	45.3	6.5	46.2
3	44.9	7	46.4
3.5	44.7	7.5	46.7
4	**44.4**	8	47.1

The simulated data curves for simultaneous evacuation strategy and social vulnerability-based staged evacuation strategy were also compared in Figure 4.6a (for I-10 east traffic), Figure 4.6b (for I-10 west traffic), and Figure 4.6c (for I-55 north traffic). In each evacuation direction, the staged evacuation strategy can always save about two hour network clearance time over the simultaneous evacuation strategy. The evacuation times across the ten runs were very consistent. At the 95% confidence level, the range of the differences in the evacuation time was only 15 minutes.

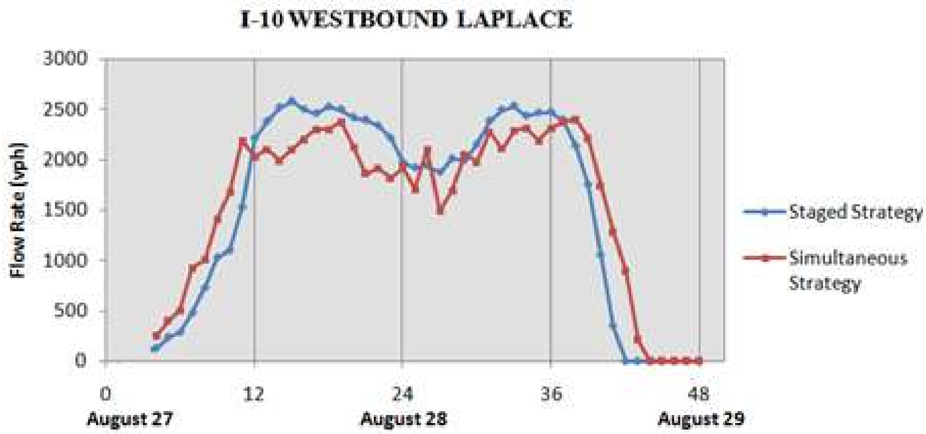
4.6 Summary of the Results

This chapter simulated and evaluated two-staged evacuation strategies (i.e. spatial vulnerability-based staged evacuation strategy and social vulnerability-based staged evacuation strategy). Before executing the simulation model, both the spatial vulnerability and the social vulnerability of the study area were calculated. For each staged evacuation strategy, the agents (i.e. census block centroids) were classified into two groups (one group with high vulnerability agents, and the other with low vulnerability). The group with high vulnerability agents would be issued the evacuation order earlier than the other group with low vulnerability agents.

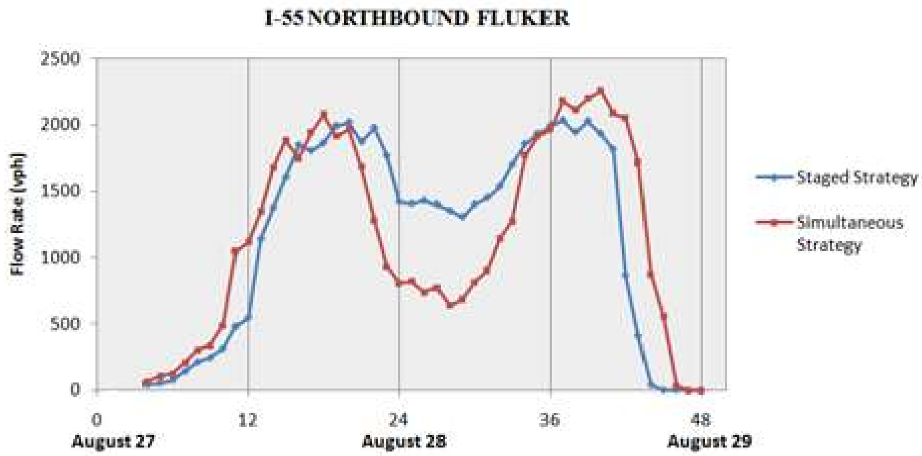
When compared with the simultaneous evacuation strategy, both staged evacuation strategies can decrease the network clearance time to a certain extent. The spatial vulnerability-based staged evacuation strategy needed 42.8 hours (save 3.6 hours from the simultaneous evacuation strategy) to evacuate all the residents in New Orleans metropolitan area, and the starting evacuation time-interval between these two groups is set to 3.5 hours for this optimal performance. The social vulnerability-based staged evacuation strategy needed 44.4 hours (save two hours from the simultaneous evacuation strategy) to evacuate all the residents in New Orleans metropolitan area, with the optimal starting evacuation time-interval between these two groups set to four hours for this optimal performance.



(a) Eastbound I-10 during Hurricane Katrina (Slidell, Louisiana)



(b) Westbound I-10 during Hurricane Katrina (LaPlace, Louisiana)



(c) Northbound I-55 during Hurricane Katrina (Fluker, Louisiana)

Figure 4.6. Simulated data for both staged evacuation strategy and simultaneous evacuation strategy

From the network clearance time point of view, the staged evacuation strategy I (spatial vulnerability-based) can save more time than the staged evacuation strategy II (social vulnerability-based). This may be because in staged evacuation strategy I, all the evacuees who would encounter serious traffic problem were in the first evacuation group, and they were issued the evacuation order earlier than the rest of the residents. This means that, since they started early, some serious traffic congestion could be avoided while evacuating.

Chapter 5 . Conclusions

5.1 Integrated Microsimulation Model

The network clearance time for the study area threatened by natural disaster is the final product of the evacuation simulation in this research. Although vehicle-based microsimulation is the finest level of simulation models existing to simulate evacuation behavior, the enormous and complex road network in a regional area and the huge number of vehicles involved in an evacuation situation prohibit its use in regional evacuation. Furthermore, calibration and running the microsimulation model for the entire area will require a long time, and may even be infeasible. So, through this research, a model was developed to integrate the vehicle-based microsimulation model with the block group centroid-based microsimulation model to solve the regional evacuation simulation problem. Both models are agent-based, so they both possess the advantages of agent-based models. The integrated model uses the census block centroid-based microsimulation to model the local part of road traffic, and uses the vehicle-based microsimulation to handle the interstate highway part of road traffic.

Since the commercial software VISSIM was adopted for the vehicle-based microsimulation, the major focus of developing the integrated microsimulation was on the census block centroid-based microsimulation model. The process of developing the census block centroid-based microsimulation model mainly includes five steps, which involve the creation and calibration of the: 1) traffic generation sub-model; 2) demand sub-model; 3) destination selection sub-model; 4) routing sub-model; and 5) a user specified plan set-up, analysis, and revision procedure (Southworth, 1991).

The output of the census block centroid-based microsimulation model can be compiled into origin-destination (OD) matrices, to serve as input to the vehicle-based microsimulation model. This input-as-output mechanism can integrate these two microsimulation models effectively. Also, the total network clearance can be obtained easily in vehicle-based microsimulation. After the integrated microsimulation model was developed, the traffic count data from Hurricane Katrina was used to calibrate and validate the model. The result shows that the integrated microsimulation model can simulate accurately the real traffic flow for regional disaster evacuation during Hurricane Katrina's evacuation.

5.2 Staged Evacuation Strategies

To ensure that the massive evacuation is really necessary, decision-makers would prefer to issue an evacuation order as late as possible with the premise that there is enough time for all the endangered people to be safely evacuated. To decrease the overall evacuation time needed, this research examined two-staged evacuation strategies. The first-staged evacuation strategy is based on spatial vulnerability. The spatial vulnerability for each census tract was calculated first and all the census block centroids were then divided into two-staged groups based on their spatial vulnerability. Then, the model let the group of census block centroids with high vulnerability evacuate first. After a time interval, an evacuation order was issued to the census block centroids in the low-vulnerability group. The second staged evacuation strategy used social vulnerability to classify the two evacuation groups.

When compared with the simultaneous evacuation strategy, both staged evacuation strategies can decrease the network clearance time to a certain extent. The spatial vulnerability-based staged evacuation strategy required 42.8 hours to evacuate all the residents in the New Orleans metropolitan area (a savings of 3.6 hours from that of the simultaneous evacuation strategy), and the starting evacuation time-interval between the two staged groups was found to be 3.5 hours for this optimal performance. The social vulnerability-based staged evacuation strategy required about 44.4 hours to evacuate all of the residents in the New Orleans metropolitan area, a saving of about two hours from that of the simultaneous evacuation strategy, and the starting evacuation time-interval between those two staged groups was found to be four hours for this optimal performance.

5.3 Contributions

The research contributes to the fields of dynamic spatial modeling, visualization, and disaster and vulnerability science. The incorporation of vulnerabilities with two types of agent-based models provides more realistic and accurate pictures of how evacuation behavior affects the evacuation strategies. The research is innovative in four aspects.

1) For the developed census block centroid-based microsimulation model, each agent can dynamically choose its evacuation destination (i.e., highway access). This represents an improvement over the traditional vehicle-based simulation.

2) By combining the census block centroid-based microsimulation model with vehicle-based microsimulation model and using social-economic information, we can extend the microsimulation from local to regional, with reasonable simulation running time and accuracy.

3) Two-staged evacuation strategies were evaluated. By using the integrated model, these two-staged evacuation strategies and simultaneous evacuation strategy were simulated and compared. Their results can inform the decision-makers on the evacuation clearance time used for each evacuation strategy.

4) Based on the census block centroid-based microsimulation model, a user-friendly simulation interface was created which can clearly show dynamically the entire traffic evacuation process to the decision-makers.

This research also has broad impacts in the following manner:

1) Although the proposed integrated agent-based model is to simulate hurricane evacuation in New Orleans area, it can also be applied to simulate other regional areas with other disasters (e.g., forest fire).

2) The MATLAB modules developed in this research, such as the Dijkstra (1959) algorithm module and the agent moving module, can be distributed widely to benefit other agent-based traffic microsimulation research.

3) The staged strategies were simulated based on the New Orleans road network, but the result can also be applied to other regions.

5.4 Future Research

Overall, this study demonstrated the feasibility and effectiveness of employing agent-based techniques when modeling evacuation traffic flow and investigating various evacuation strategies. However, many variables were not considered in the simulations, and a number of issues are subject to future research.

First, all the input data for the census block centroid-based microisimulation model is based on raster imagery. Since a single-layer raster image is saved as a two-dimensional matrix in a computer, this makes the dynamic tracking easily fulfilled for any agent. However, most of the current road network data available is in vector-based format. Also, as far as the geometry is concerned, the vector data is easy to be manipulated (e.g., add or delete one link from the road network), and usually requires less storage space than a rasterized image. These advantages will make more detailed local road network input possible for traffic simulation. Furthermore, the input data would not be limited by the spatial resolution issue anymore, which can affect the simulation result accuracy. In sum, if the vector format data model is used for input (both agent locations and road network) in the census block centroid-based microsimulation model, more reliable and accurate simulation results would be obtained with shorter simulation model running time.

Second, the data used to calibrate and validate the simulation model are only from Hurricane Katrina in this research. It would improve the creditability of the developed simulation model if the model could be validated with most current traffic count data from Hurricane Gustav. However, to simulate the traffic flow for Hurricane Gustav, the current census data for New Orleans should also be used since the population in New Orleans changed dramatically after Hurricane Katrina.

Third, this research only simulated and evaluated the effectiveness in terms of network clearance time of three evacuation strategies: simultaneous evacuation strategy, spatial vulnerability-based staged evacuation strategy, and social vulnerability-based staged evacuation strategy. Other applicable and reasonable evacuation strategies would be tested to improve the evacuation efficiency.

Last but not least, the integrated microsimulation model and the evacuation strategies were developed and tested for hurricane evacuation in New Orleans in this research, but the effectiveness and applicability of the model and the evacuation strategies could also be tested in other regional areas with different natural or man-made disaster evacuations.

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Appendix A

Technical Aspects of the Census Block Centroid Based Microsimulation Model

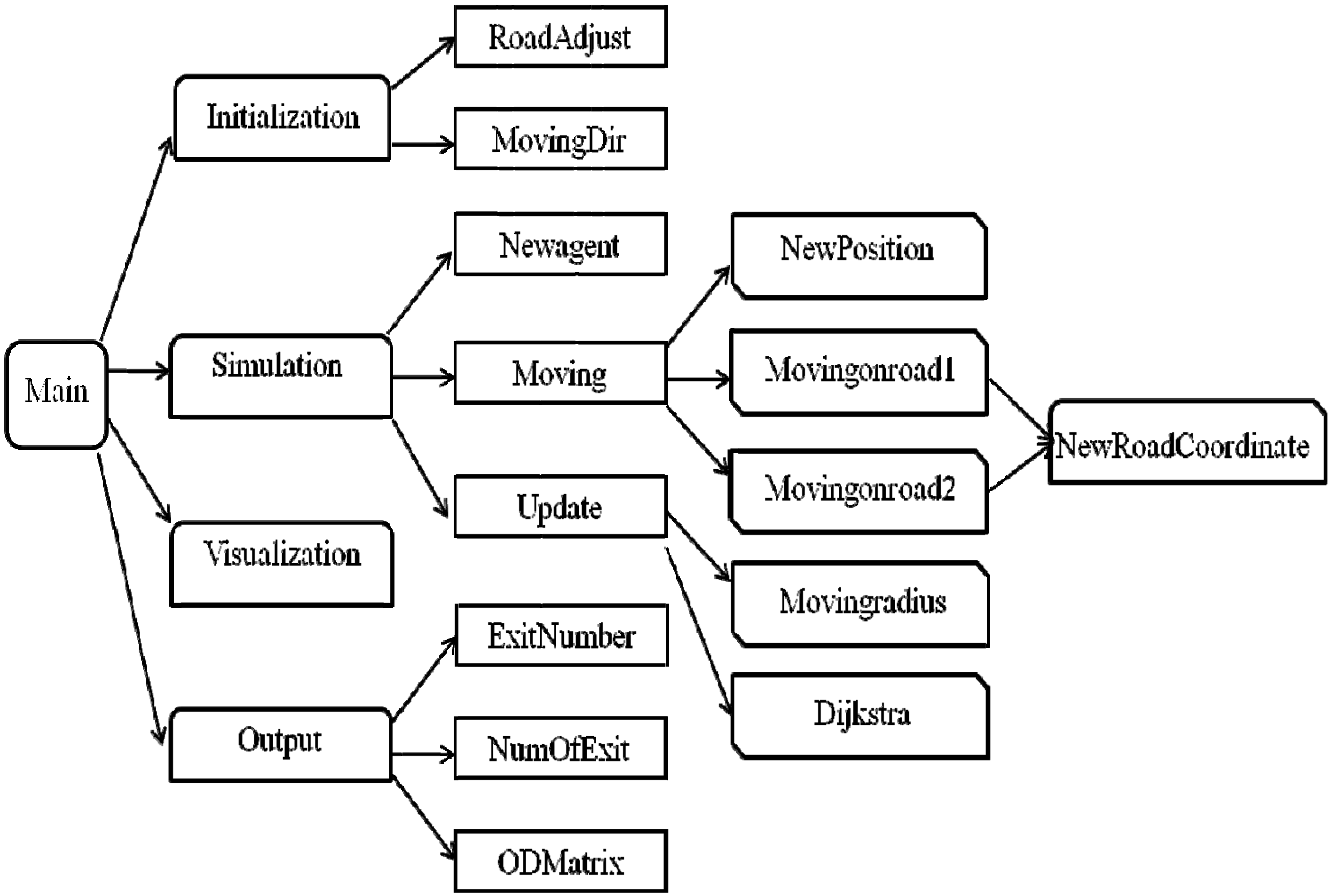
This section discusses important technical aspects of the census block centroid based microsimulation model for simulating local traffic during regional disaster evacuation. The model capability and organization are also provided.

As part of the integrated microsimulation model, which is designed for the analysis and evaluation of the evacuation strategies, this census block centroid-based model simulates the local major road traffic in regional areas. This model is treated as a microscopic simulation model which considers the status of each agent individually rather than by aggregating them. During simulation, the dynamic status of each agent is affected both by adjacent agents and environment (i.e. road network). The input of this agent-based microsimulation model includes agents (census block centroids) and its environment (local major road network and its property), and the output are O-D matrices, which store the number of vehicles that arrive at each given highway entrance during every time period (e.g. hour). Detailed information about the network geometry and its property (e.g. number of lanes, free speed, and capacity on each link), is part of the input data. Furthermore, the movement of each agent at each time step can be spotted during simulation.

This census block centroid based microsimulation model involves one main routine and four levels of subroutines. The structure of the whole model and its relationship to each other are shown in the following figure.

Main Program

The basic function of the main program is to organize the framework of this agent-based model and to invoke the subroutines. It also starts the agent evacuation phase and controls the



General Framework of Census Block Centroid Microsimulation model

model running until the end of the simulation process (i.e. all the agents arrive at their desired highway entrances). The global variables and the subroutine parameters such as total number of agents in the study area and simulation time resolution (30 seconds in this study) are defined here.

As shown in the figure above, the mechanism of the program for this model involves four major levels of subroutines. Among them, the second level involves initialization subroutine, simulation subroutine, visualization subroutine, and output subroutine. The third level subroutines are: RoadAdjust subroutine, MovingDir subroutine, Newagent subroutine, Moving subroutine, Update subroutine, ExitNumber subroutine, NumOfExit subroutine, and ODMatrix subroutine. The fourth level includes five subroutines namely: NewPosition subroutine, Movingonroad1 subroutine, Movingonroad2 subroutine, Movingradius subroutine, and Dijkstra subroutine. The fifth level involves the NewRoadCoordinate subroutine. The functionality and mechanism of the various levels of subroutines are discussed in the following sections.

Initialization Subroutine (second level)

The initialization subroutine mainly performs the following tasks:

1) Import all the attributes for road network, nodes, and agent. The local major road for this simulation model is been transformed from feature classes to raster datasets with the resolution of about 13.456 meters per pixel for both horizontal and vertical direction, in ERDAS IMAGINE. A total of 3321 rows and 2107 volumes in the result raster image. The reason to convert the feature class into a raster image is that the raster image can be treated as matrix and thus can be handled much easier in the MATLAB ™ programming IDE environment.

2) To invoke the RoadAdjust subroutine and MovingDir Subroutine.

RoadAdjust Subroutine (third level)

In the local road network raster image, one link/road segment is composed of several adjacent cells in the raster image matrix. The initial cell value for each link is a unique integer whose road network raster image is converted from a road network feature class. If we use the raster image with the same integer value for each link is used to simulate the traffic flow, it is difficult to control the movement of agents traveling along the same road link. So, to make the agents manageable in this raster image, this RoadAdjust subroutine is developed. It uses different float numbers rather than the same integer to represent all the cells of any single road segment.

Consider, for example, the network raster image link ID number 39, which is composed of 64 cells. The cell values at the beginning and at the end of the link will be the smallest (39.001) and the largest (39.064). Any cell in the middle of this link has a unique float number between the smallest and largest. In case of driving from largest value cell to the smallest value cell along one single road link, the cell value should be large for locations near driving distance. Another advantage of making the cells in one link have different float values is to know the moving direction for each agent on the link. This means when an agent drives on this link, depending on the cell values, the driving direction for this agent can be recorded until it reaches the end of this road link.

MovingDir Subroutine (third level)

This subroutine decides the final destination direction (i.e. east, west, north, US-61, or LA-1) f each agent before simulation begins.

Simulation Subroutine (second level)

This subroutine and those third to fifth level subroutines invoked by it are the core and most complex part of the entire agent-based model. It simulates agent movement from the beginning of disaster evacuation until all the agents arrive at their desired highway entrances. To fulfill this purpose, it includes three third-level subroutines and five forth-level subroutines as well as one fifth- level subroutine.

Newagent Subroutine (third level)

The purpose of this subroutine is to calculate the number of agents to evacuate from their initial locations at each time step, and to decide the IDs of these agents. In this study, it is assumed there is no priority of start time for any agent if no mandatory regulation is applied. So, a random function in MATLAB is utilized to choose the agents' IDs at each time step.

Moving Subroutine (third level)

This subroutine is to solve the rules of how the agents travel throughout the evacuation process, and it involves three fourth-level subroutines: NewPosition subroutine, Movingonroad1 subroutine, and Movingonroad2 subroutine.

NewPosition Subroutine (fourth level)

The initial positions of the agents in the census block centroid microsimulation model are in the middle of all the census blocks, so most of these agents are not on any local major road segment before they start to move. A method is developed to let these off-road agents find and drive onto road network while they are still moving toward road network.

In this study, it is assumed that, at any time step, if one agent is moving but still does not arrive at road network, the Euclidean distances from its current position to the nearest road segment on each direction (i.e. east, south, west, and north) are compared, and then the road with the nearest distance is chosen as the destined road segment. This agent is then moved one step distance toward it. In this moving process, it is assumed that the moving speed of any off road agent is 25 km/hour at any time, so one step distance for 30-second (i.e. simulation resolution) should be about 208 meters. In the following steps, this agent would repeat the same comparison process, and choose the nearest at every time step until it arrives at a road segment. After arriving at a road segment at any location, it should drive directly onto next step.

Movingonroad1 Subroutine and Movingonroad2 Subroutine (fourth level)

These two subroutines both deal with the way agents travel along the road network. For any road link in the rasterized road link image, the value of all the cells composing one single link should continuously increase 0.001 from one link end with smallest cell value to the other end with largest cell value.

The only difference between these two subroutines is driving direction: one subroutine handles drive agents along road segment from the direction of small end cell value to large end cell value, while the other subroutine handles drive agents with the opposite driving direction on the same road link (i.e. from the direction of large end cell value to small end cell value).

For every road segment at every time step, by using the “travel radius” obtained from Movingradius subroutine, we can move the agents, who are driving on road links, to their proper positions in this subroutine. When an agent is moving along one road link, the moving distance from the position at the former time step is one single “travel radius” if without arriving at an intersection.

Yet if an agent comes across an intersection, the Newroadcorridiate subroutine, which is the only fifth level subroutine in this agent-based model, will be invoked to decide the new position of this agent at current time step.

NewRoadCoordinate Subroutine (fifth level)

When an agent moves along a road link and arrives at an intersection at current time step, the NewRoadCoordinate subroutine is invoked to decide the next driving link and the proper moving position at this time step.

To fulfill this purpose, two issues need to be considered when an agent arrives at an intersection. First, if this intersection is a highway access, which means that this agent has arrived its destination, then records the number of vehicles represented by this agent into the corresponding result OD matrix. Second, if this intersection is not a highway access, the agent would evaluate all the possible paths that can reach any desired highway entrance, and finally chooses the nearest one in terms of the travel time to drive onto.

Update Subroutine (third level)

After one time step simulation of the movement for all the agents, the traffic information should be updated. This update includes the travel speed on each road segment and the nearest distances to each final destination (e.g. east, west, or north) for each node.

Movingradius Subroutine (fourth level)

The moving radius (i.e. the moving distance for one time step) on each road segment can be obtained by calculating the travel speed at the road segment first, described in section 3.3.1.

Dijkstra Subroutine (fourth level)

This subroutine calculates the shortest travel time to desired highway entrance for each node, and it should be updated every time step.

Visualization Subroutine (second level)

With the background of local major road network, the movement of all the agents can be visualized dynamically in MATLAB with the updated agent locations at each time step.

Output Subroutine (second level)

This census block centroid based microsimulation model is only the first part of the integrated simulation model in this study which can be used to simulate regional disaster evacuation. Hence the number of vehicles that arrive at each highway access during every time interval (e.g. an hour) must be recorded. After that, these recorded numbers are assembled as O-D matrices, which are utilized as the input of the vehicle-based microsimulation model.

This vehicle-based microsimulation model is used to simulate the interstate highway part of traffic in the regional disaster evacuation simulation.

ExitNumber Subroutine and NumOfExit Subroutine (third level)

The output of census block centroid microsimulation model in this study is a series of O-D matrices. However, to create these O-D matrices, we must first use the NumOfExit subroutine to find out the number of highway entrances (one link end that can enter highway is deemed as a highway entrance) in the local major road network, and then use the ExitNumber subroutine to assign a unique ID to each of these highway entrances. The second level simulation subroutine, which measures at every time step (30 seconds) the number of vehicles that arrive at any highway entrance in this local major road network would also be used.

ODMatrix Subroutine (third level)

In this census block centroid based microsimulation model, to create the input O-D matrices for the vehicle based microsimulation model, the number of vehicles that arrive at each final destination (i.e. east, west, and north) during each time interval (60 minutes in this study) of every highway entrance is recorded. However, several highway entrances in this census block centroid simulation model may merge to the same one (from the interstate highway point of view) in the vehicle based microsimulation model. This exists because the end of several road links (recorded by different ID number in census block centroid based microsimulation model) may all use the same highway access (e.g. I-10 exit 226) in vehicle based microsimulation model.

The dimension of each input O-D matrix is m × m (i.e. m rows × m columns) in the highway simulation microsimulation model, and the value of “m” is the number of highway entrances in the vehicle-based microsimulation model. As a matter of fact, in this m × m matrix, only three columns (represent three final evacuation directions: east, west, and north) are effective. The cell values in the other columns are all zeros in this matrix. So in this ODMatrix subroutine, the exit matrix (dimension is $n \times 3$, and n is the number of exits in local major road network while 3 represents east, west, and north) recorded in census block centroid microsimulation model is being transformed into the $m \times m$ matrix needed in vehicle based microsimulation to simulate the traffic flow in interstate highway.

Technical Section Summary

These described routines in this Appendix are all written in MATLAB programming language. The computer memory needed for entire program is around 250 Megabytes. With this capacity, a network with up to 438 links and 310 nodes is executed for the New Orleans metropolitan area. One single model running time on a workstation with a dual core 2.41 GHz CPU and 8 GB RAM is about 5 hours for this census block centroid based microsimulation model.

Appendix B

Approximate Trip Productions at Different Times of the Day

Given that the traffic volume graph of each day usually follows the shape of sine wave, we tried to incorporate a sine function into this traffic loading equation. The basic form of a sine wave is:

$$Y= A * \sin (X) \qquad (1)$$

Where, A is peak deviation from centre for this wave, and X is the adjusted simulation time.

At any time, the traffic volumes have a non-negative volume (i.e. greater than or equal to zero) for each link during evacuation, so we assume that Y has a value range of $d <= Y <= c$ (c and d are two parameters need to be calibrated before model execution) in equation 1. Since 1 is the largest value for sin(X), parameter A should equal c. We assume that the simulation time step has a linear relationship with the X (i.e. adjusted simulation time). So,

$$X= e*a + f \qquad (2)$$

And thus equation 1 can be rewritten as:

$$Y= c* \sin (e*a +f) \qquad (3)$$

A, *e* and *f* are the parameters in equation 3, while lower-case *a* is the variable of current simulation time step, while *Y* is the corresponding value of the sine wave. One single cycle for this sine curve is 24 hours. However, two sets of these parameter values should be obtained for both the first 12 hours of a day and the following 12 hours of a day respectively.

To calculate the parameters in equation 3 for the first 12 hours of a day ($0<= a <= 12*60$ minutes), the corresponding two known points values (i.e. time step=0 and time step= 12*60) on the sine wave can be used.

1) At the time step =0: which means $a = 0$, $Y=d$ (the minimum value), and then equation 3 could be rewritten as:

Arcsine (d/c) = e *0 + f (4)

So f equals arcsine (d/c);

2) From the time step 12*60: which means a = 12 *60, $Y=c$ (the maximum value), X equals with arcsine (c/c) from equation 1, and then equation 2 could be rewritten as:

Arcsine (c/c) = e* (12*60) + arcsine (d/c) (5)

So parameter e = (arcsine (c/c) – arcsine (d/c))/ (12*60). And then we can obtain any Y value for the first 12 hours of a day for each simulation time step by using equation 3 with the parameters e, and f obtained above.

While for the situation of the next half 12 hours of a day (12*60 minutes < a < 24*60 minutes), another set of values for parameters in equation 3 should be obtained. We can also calculate these parameter values in equation 3 by using the two corresponding known points (i.e. time step=12*60+1 and time step=24*60).

1) From the time step=12*60+1: which means a = 12*60+1, $Y=c$ (the maximum value), $A=c$, then equation 3 can be rewritten as:

Arcsine (c/c) = e * (12*60+1) + f (6)

2) From the time step=24*60: which means a =24*60, $Y = d$ (the minimum value), A=c, X equals arcsine (d/c) from equation 1, equation 2 can be rewritten as:

Arcsine (d/c) = e * (24*60) + f (7)

From equations 6 and 7, the parameters of e and f can be calculated: e = (arcsine (d/c) – arcsine (c/c)) / 719; f ≈ arcsine (d/c) - (arcsine (d/c) – arcsine (c/c)) *2 = 2*arcsine (c/c) – arcsine (d/c).

Finally, we can summarize the equation 3 into the following format:

$$
\begin{cases}
Y=c * \sin\left((\text{arsine}(c/c) - \text{arcsine}(d/c)) / (12*60) * a + \text{arcsine}(d/c)\right) \quad (8) \\
\qquad\qquad (\text{When } 0{:}00\text{am} < a <= 12{:}00\text{pm}) \\
Y=c * \sin\left(((\text{arcsine}(d/c) - \text{arcsine}(c/c))/719) * a + 2*\text{arcsine}(c/c) - \text{arcsine}(d/c)\right) \quad (9) \\
\qquad\qquad (\text{When } 12{:}00\text{pm} < a <= 24{:}00\text{pm})
\end{cases}
$$

If we integrate the Y variable into the loading rate equation, then the new loading rate equation would be as follows, and three variables (i.e. z, c, and d) should be calibrated in this equation:

$$\text{Ratio} = 1/ \{1+\exp [-z*(a-T)*Y]\} \qquad (10)$$

Vita

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