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MBTC DHS 1102 - Simulating Large-Scale Evacuation Scenarios in Commercial Shopping Districts – Methodologies and Case Study

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Executive Summary

Large-scale regional evacuation is an important component of homeland security emergency response planning; however, evacuations involving large commercial shopping areas have not been a major focus area for research initiatives. This report explores the state of art for modeling large-scale evacuations within geographic areas that contain commercial shopping districts. The focus of the report is on microscopic simulation methods. A systematic methodology for simulating evacuations induced by emergencies is examined within the context of a case study involving the evacuation of parking lots within a commercial shopping district. A base model for background traffic was constructed and validated in order to represent real traffic conditions. Six evacuation scenarios were developed and explored within simulation experiments by varying factors involving the occupancy rate of parking lots and background traffic levels. The performance of vehicles attempting to evacuate the areas is captured in terms of an evacuation risk profile involving the most problematic parking lots and areas where traffic bottlenecks are projected to occur.

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1. INTRODUCTION

The planning of large-scale evacuation has become an important area of emphasis for emergency planners. Large-scale evacuation involves the movement of people and resources both to escape the disaster and to respond to the disaster. Such disasters include natural and man-made events (e.g. earthquakes, tsunami, wildfire, radioactive release, and terrorist attacks). In areas prone to emergency events, such as wildfire interfaces, canyon communities, large shopping malls or islands offshore, the preplanning for evacuation is necessary and crucial. For instance, more than twenty people were killed in the Oakland Hill wildfire of 1991, where most of them lost their lives within no more than half an hour after the fire. (Church and Sexton, 2002) An unprecedented devastating tsunami hit Indonesia in 2004, causing more than 16,000 deaths and thousands of homeless people, due to lack of tsunami warning systems and well-prepared evacuation plans. (Asian Development Bank, 2006) Piqued by these emergency scenarios, researchers have begun to develop optimal evacuation strategies, where numerous relevant problems emerge with a central issue concerning how best to simulate the processes and assess the risk of emergency plans.

The analysis of evacuation situations started with static methodologies such as the bulk lane demand (Cova and Church, 1997). This is often done as a preliminary analysis and because of the lack of computational resources. These methods have limitations attributed to the fact that the evacuation process is dynamic with chaos and instability, rather than static. Evacuation modeling requires the details of the movement of vehicles and people, as well as the topography within the emergency planning zones, in order to realistically represent the situation. In the past twenty years, advancements in computer technology have given rise to high fidelity simulation, which make it possible to model the details and complexity of evacuation scenarios. Micro simulation, with the ability to track individual movements of resources as well as their collective behavior, has been successfully applied to various evacuation situations.

Modeling methodologies used in evacuation have received much attention in the literature. The modeling of mid to large range evacuations (e.g. neighborhoods, parking areas, large building structures, commercial districts, etc.) remains an open area of research due to the fact that more detail as to the vehicle and pedestrian movement is required. Normally, most studies are based on the estimates of the evacuation of vehicles firstly according to the population, vehicle occupancy, and vehicle usage within the emergency planning area. Often assumptions are made that all the vehicles will be released directly into the traffic flows, without considering the detailed movements within parking structures (e.g. vehicles backing out of parking spots or driveways, and the interaction with pedestrians). These assumptions are made because of the computational burden of this analysis and because adequate modeling of these processes has not yet occurred. It should be clear that the detailed modeling of how the vehicles get into the road network is necessary because of the potential effects that this time can have on emergency plans.

This exploratory research project focuses on the application of current evacuation simulation technology, offering a systematic methodology concerning the evacuation induced by emergencies from large scale commercial shopping districts with parking lots via a case study analysis. The overall goal of this exploratory study is to investigate methods for simulating evacuations caused by emergency events such as chemical pollution and disasters that threatening the safety of the public. There are two sub-objectives 1) understand the state of the art for modeling large scale evacuations, especially via simulation, and 2) developing, applying, testing, and validating the effectiveness of simulation models on realistic evacuation scenarios. This research project analyzes the state of the art for this type of modeling and makes recommendations for improving evacuation modeling methodologies. In addition, through the case-study, recommendations are made to improve the evacuation of the examined area.

This report is organized into the following sections. Section 2 covers background and literature within the area. Section 3 describes modeling methodologies including data analysis, data collection, model building, and model calibration within the context of the case study. Section 4 addresses model experimentation and result analysis. Finally, directions for future research for large-scale evacuation are identified.

2. BACKGROUND AND LITERATURE REVIEW

Evacuation presents the immediate large-scale movement of resources such as vehicles and people. An evacuation can be separated into two categories by size of the planning region, including neighborhood evacuation and regional evacuation. The former is a smaller area evacuation, such as community evacuation, building evacuation with parking lots, etc. The latter involves urban evacuation such as that associated with hurricanes involving the evacuation of an entire city.

Generally, there are five phases within the evacuation process: emergency detection, evacuation decision, emergency warning, and resources mobilization. Evacuation plans are made to maximize the safety of the evacuees but minimize the total evacuation time for the entire region through various operational strategies including but not limited to traffic light control, traffic flow control, and evacuation sequencing. Because of its ability to represent detailed dynamics, simulation is an important analysis technique within evacuation modeling.

2.1. Evacuation simulation

The methodologies and the application of simulation within emergency planning have been under development for many years. Generally, there are three types of simulation approaches: micro-simulation, meso-simulation and macro-simulation. Micro-simulation tracks the detailed movement and interaction of individual entities on the road, whereas macro-simulation models the aggregate behavior of traffic flows based on equations stemmed from analogies with fluid flows. Meso-simulation, a compromise between micro-simulators and macro-simulators, focuses on the movement of platoons of vehicles. (Pidd *et al.*,1996; Southworth, 1991; Sheffi *et al.*, 1982)

At the beginning of the use of simulation, only aggregate simulation was used to simulate network traffic movement because of the constraint of limited computational resources. One of the most noticeable applications of evacuation simulation was presented by Sheffi *et al.* (1982). In order to estimate the clearance time in the evacuation of the area around nuclear power plants, Sheffi *et al.* (1982) described a macro simulation model, NETVACI which considered the problem of dynamic traffic assignments by exploring the mathematical relationships among traffic flows, speeds, densities, and queues. Overall, there were two logical units in the model; one was link pass, the other node pass, which specifically handled the traffic flows in the road and intersections, respectively. As the authors described, NETVACI simulated the drivers' choice for certain routes based on two factors including link familiarity and myopic behavior. The probability of selecting a route was determined by the driver's preference and traffic speed in that link at each simulation interval. However, in real evacuations the selection of routes is much more complicated and prone to being affected by other factors such as the specific environment and conditions, evacuation plans, and other uncertainty factors. In addition, the simulator assumed that the vehicles within a given time interval make route choices as a whole, which probably does not adequately represent reality. Consider a group of drivers approaching an intersection and coincidently there is congestion in a certain link. In this situation, the drivers probably do not select the link because of the congestion in this time interval; however, it is highly possible that the congestion would be dissipated when the drivers at the end of the group arrived at the intersection. The choice made before, therefore, can not represent the situation in this time interval.

Under development in technology and methodologies applied to evacuation planning, Southworth (1991) offered a systematic review of regional evacuation modeling. The author described an evacuation study as consisting of five separate processes: trip demand generation, evacuation departure timing, destination choice, routing assignment, and building-up of evacuation plan and analysis. Based on these stages, evacuation theories and simulation models were introduced. The author stated that the network coding, spatial and temporal distribution of population, and vehicle utilization were the emphasis of the trip generation. Since collecting data containing population distributions involves considerable difficulty and uncertainty, especially in varying location and time of day, it was common and representative that "worst case" or "average case" evacuation scenarios, including various population distribution and vehicle utility, were used to approximately capture the evacuation situations. (Southworth, 1991)

In the paper, the author also summarized three approaches used to model the route selection process: myopic route assignment, an optimization model based route assignment, and pre-specified route assignment. Moreover, the comparison of the static route assignment versus the dynamic route assignment was presented. He argued that the dynamic assignment models were able to model time dependent traffic load rate and route selection, because the static assignment model assumed that the traffic loading rate was steady in the simulation intervals.

With advances in technology, computation capability has improved the application of micro-simulators. A sensitivity analysis of total evacuation time was done by Sinuany-Stern and Stern (1993) with a special simulation language (SLAM II). Based on an evacuation case study of a small city, they found that the total evacuation time was susceptible to the route selection mechanisms as well as several traffic factors including friction with pedestrians, intersection traversing time and population size. Two route choice methods, shortest path and “myopic” view, were introduced to model the evacuation. They concluded that the simulation results were more realistic if the driver selected links with the maximal distance from the last car on that road instead of the shortest path. In addition, it was found that the simulation results would match better with reality, when considering the interaction with pedestrians and a uniform distribution of intersection traversing time.

In the initial stage of evacuation, the authors assumed that the time consumed in the warning dissemination and evacuation preparation was deterministic and evacuees engaged in evacuating simultaneously; nonetheless, traffic loading patterns to the network was stochastic.

During an evacuation, instability and perturbation may be ubiquitous in the affected region. How to model the individual behaviors in response to evacuation is the primary issue, which has been studied by many researchers during last twenty years. Normally it will take some time before the public begins to mobilize within the affected region. Typically, the evacuation time can be partitioned into four stages involving decision time, notification time, preparation time and network clearance time (Urbanik *et al.*, 1980). Once the emergency happens such as a terrorist attack, the authorities have to make a decision of whether to evacuate or not. Once the evacuation is necessary, then the evacuation order information has to be disseminated, followed by the preparation and mobilization of the people within the affected area.

The response time or departure time is from detecting the emergency to starting evacuation. Southworth (1991) stated that there were four approaches used to capture the response behavior of evacuees once the hazard events happened, including derivation from past evacuation data, intention survey to potential evacuees, experts evaluation, and simulation based on the diffusion of emergency warning information. The process of the emergency warning dissemination was analogous to other common information scenarios without considering the time constraint (Rogers and Sorensen, 1991). Rogers and Sorensen (1991) compared the effectiveness of various emergency warning mechanisms including sirens and alarms, tone-alert radios, telephone systems and dual media systems. Rogers and Sorensen (1991) made an assumption that the warning dissipation process could be captured by a logistic curve or an S-shaped curve, where the cumulative percentage of warning recipients was modeled as a function of time. Sorensen (1991) studied factors associated with individual variation in departure time, and concluded that departure time was determined by the mode of the warning system, spatial distribution of the population and type of living structure.

Different from previous large-scale modeling, neighborhood evacuation analysis requires the spatial details in the affected area, and micro-simulators are the most detailed transportation simulation alternatives for this type of analysis (Cova and Johnson, 2002). Church and Sexton (2002) applied microscopic simulation to the evacuation of a neighborhood named Mission Canyon. Based on the distinct topography in the affected region, combinatorial scenarios, considering household vehicles levels, opening another road exit, and traffic control plans, had been developed. The project evaluated whether the current road capacity could support the evacuation traffic demand, given that a wildfire happened in the region. According to the comparison among the simulation results, the authors concluded that providing an alternative road exit and implementing traffic control plans in both intersections and main roads can highly reduce the clearing time.

However, there are several shortcomings in the paper. The authors simply assumed that the percentage of vehicles loading on traffic networks at each time interval was fixed. Actually it is a random value and hence the discrete distribution does not fully capture the characteristics of the evacuation process. Additionally, only three deterministic levels of vehicles per household were considered in the simulation model, which was also stochastic.

In the case study of a hurricane evacuation in the Cape May County (National Center for Transportation and Industrial Productivity [NCTIP], 2007), emergency planning zones were partitioned into small adjacent zones for trip generation. One noticeable scenario was the development of a traffic lane contra-flow plan taken into consideration within the simulation modeling. Lane contra-flow plans alter the direction of normal traffic flow in certain lanes, usually for mitigating traffic congestion in peak hours or evacuation. A logistic curve was assumed to be appropriate in modeling the traffic loading pattern. Based on the how fast the evacuee responded to the evacuation order, three types of response curves were presented: low, medium and slow. NCTIP (2007) also described that vehicles rate per household was estimated through two strategies. One was the data based on the 2000 census; the other was derived from an increased owning rates model. In order to minimize or eliminate the uncertainty or variability of the result, multiple simulation runs were performed for the reason that the micro-simulation is a stochastic process.

For developing an emergency plan in a neighborhood-scale evacuation, Cova and Johnson (2002) presented a methodology framework, which consisted of two parts, one was evacuation scenarios generation, the other micro-simulator and GIS. Evacuation scenarios generation was used to generate trip matrices, response time and destination choice, and then the micro-simulator and geographic information systems (GIS) were employed to simulate the traffic environments including network construction, route choice and result visualization.

The authors argued that most researchers took interest in the aggregate performance in the evacuation such as the total network clearance time, while ignoring the importance of disaggregate performance like household level evacuation, which probably failed to distinguish the spatial variation in the different parts of the affected area. (Cova and Johnson, 2002)

During trip generation, instead of quantifying the number of the vehicles in each household by determining the parameters such as household occupancy rate, the number of vehicles per house unit and the number of house units, the authors introduced a Poisson distribution to simulate the number of vehicles in each house at different times of the day. Similarly, the reverse Poisson distribution was also employed to simulate the departing time of evacuees in the neighborhood. The author described four methods for destination choice: closest exit assignment, traffic data-based approach, manually established method, and probabilistic approach.

A case study was presented in the paper for a community in a fire-prone canyon, where the mean numbers of evacuating vehicles per household and the mean vehicle departure time, as well as a proposed access were taken into consideration to establish different scenarios. The spatial variation in travel time of each household was mapped using GIS to indicate how much travel time was needed for specific household and which evacuees suffered from serious evacuation difficulty.

Constrained by limited computation resources and critical requirements for meticulous inputs, micro-simulators have been mainly applied to small areas. Piqued by the realism, an increasing number of researchers have turned their attention to modeling urban scale traffic networks through micro simulations. One example of a micro-simulation of regional traffic networks was presented by Satinnam *et al.* (2005), where a micro scale simulator was used to evaluate the effectiveness of the proposed traffic policies in Khon Kaen city.

Another simulation model using MITSIMLab was constructed to simulate the evacuation for a neighborhood region, Los Alamos National Laboratory (LANL). Several scenarios were considered, such as traffic restriction on certain routes, closing the current roads and opening a new road. Based the percentage of the evacuees living in different locations outside the affected area, a simple partition assumption in selecting destinations was made to construct the O-D matrix. Through the identification of congestion locations and the time-dependent curve of the percentage of population evacuated, a comparison was made to evaluate the effectiveness of different evacuation strategies. (Jha *et al.*, 2004)

Traditionally, most researchers assume that the trip demand can be estimated by using the evacuation participation rate in the traffic analysis zones and that evacuation departure times can be modeled by a known response or S-curve. As an alternative, however, Fu and Wilmot (2004) assumed that the uncertainty of evacuation decision made by evacuees could be captured in sequential time intervals by a binary logic model based on the factors of household type, hurricane characteristics, evacuation orders by authorities, and time periods in a day during a hurricane evacuation. Based on the model developed, the dynamic demand assignment was achieved to model the evacuation demand in the initial stage of the evacuation. The model results also indicated that the probability of evacuation will be affected by the time of day, that is, lower at night, increase in the morning and peaking in the afternoon.

For evaluating the minimum clearance time and estimating the quantity and locations of the evacuees in specific time intervals with VISSIM V3.70, Chen *et al.* (2006) developed a micro-scale simulation which was able to simulate the collective behavior of a group by capturing the individual behavior of resources including vehicles, pedestrians and their interactions. Based on the Miller study (Miller Consulting, 2001) and a formula developed by Nelson *et al.* (1989), the number of vehicles in each evacuation zones was determined by considering several factors associated with car ownership, households quantity, household participation ratio, house occupancy rate, and vehicle usage level. Two response curves were used to simulate the departing time of evacuees, involving the late response curve developed by Baker (2000) and realistic response curves deduced from the evacuation of Hurricane George. It was found that the evacuation plan with the realistic response curve took less time than the one with the late response curve, and the number of people trapped in the specific locations could be estimated based on the simulation results, given that all the routes were damaged and could not be used to evacuate after the evacuation order was made for a certain time.

Different from previous studies, Chen and Zhan (2008) turned their attention to determining the effectiveness of evacuation strategies including simultaneous and staged evacuation. The authors described that the all the residents were informed and evacuated at the same time in the simultaneous strategy, whereas, in the staged evacuation, the affected area was divided into several small zones and the residents were arranged to evacuate sequentially.

An agent-based modeling tool, Paramics, was used to simulate the traffic networks operation at a microscopic level for tracking the movements of individual vehicles and their interactions. By modeling three types of road structures including a grid road, a ring road and a real road structure under various levels of population density in the emergency plan zones (EPZ), it was found that the simultaneous strategy is advantageous when the population density is low regardless of the road structure, whereas if the population density increased to certain level, the staged evacuation time was much less within a grid structure and the real road structure. (Chen and Zhan, 2008)

There are several potential deficiencies within the paper. First, the study scope was only a small area. Thus, the conclusions concerning larger evacuations are limited. Second, the paper did not take into consideration the departing time of evacuees, which represents the reaction time from getting the evacuation order to evacuate, and should be added to the evacuation time in order to better estimate the time needed. Third, the rate of vehicles per household was deterministic. In the light of simplicity and representativeness, it may be reasonable. The number of vehicles per household can fluctuate at different time of the day and for different households. Third, in the dynamic route choice, the authors simply assumed that all the drivers were familiar with route information, which is not necessarily true and the unfamiliarity factors should be also considered. Last but not least, no pedestrian interaction was simulated in the traffic flows.

Instead of using microscopic packages as tools to simulate the evacuation process, Liu *et al.* (2008) created a special corridor-based evacuation system integrating operation strategies in route choice, contra-flow plan design, intersection signal control, staged evacuation and interaction between pedestrians and individual cars. As the authors described, the system consisted of five models: input model, database model, optimization model, online macro simulators model and output model. The input model tackled with the network coding and specifying evacuation demand, data of which was stored in the database model. The optimization model was used to generate effective evacuation plans including route selection, contra-flow control and intersection signal timing. Based on the specified network structure and evacuation plans, an online macro-simulator was used to visualize the evacuation process and evaluate the corresponding control plans.

With the emergence of GIS (Geographic Information System), the area of integrating GIS with simulation systems has received more and more attention in emergency planning. Generally, there are two primary functions in GIS. One is static analysis including mapping and providing the mathematical analysis of information. The other is dynamic analysis, where the GIS is used as a data base for simulation and displaying the dynamic simulation results. Radke *et al.* (2000) argued that GIS could be used in the preparedness and response process of emergencies including natural related and human induced hazards. Another notable application of GIS in evacuation planning was presented by Pidd *et al.* (1996). In the paper, a spatial decision support system (SDSS), linking a GIS (ARC/INFO) with a special micro-simulator, was introduced to support the development of contingency plan for evacuation. In the system, GIS is used for two purposes. One was providing data for the simulator, such as topography and spatial population distribution. The other was for displaying results of simulation runs. The micro-simulator was written in object-oriented C++, simulating the traffic flow on the route; however, the model assumed that the road networks were grid structured and individual vehicles used myopic behavior during route selection. In addition, they did not take into consideration the interaction between vehicles, especially with respect to congestion.

Calibration procedures are an indispensable part in simulation modeling, directly determining the effectiveness and validation of the simulation results, since not all factors can be presented by the default capability of simulation packages. For instance, it is highly possible that the road structure within the packages must be modified in order to better reproduce real specific networks. Within a simulation of the city of Irvine in southern California, by Chu (2003), the authors introduced a systematic and comprehensive calibration procedure including driving behavior calibration, route choice calibration, dynamic OD estimate calibration, and fine-tuning calibration. The GEH statistic was employed to sort the traffic data and validate the results within OD demand estimates. Two optimization functions were provided to fine-tune the process in order to evaluate the simulation results. In addition, the traffic analysis toolbox prepared by USDOT (2004) can be referred to as a general guide during the calibration procedure of micro-scale simulations for the aspects of capacity, route choice and system performance calibration.

As an overview to previous literature, there is no doubt that the modeling methodologies in large area evacuation or neighborhood evacuation have been given more and more attention in the past decades. This project focuses on presenting a systematic methodology for evacuation modeling including key evacuation modeling issues such as parking lot simulation, trip generation, and departure time modeling.

2.2. Parking lot modeling

While the efficiency and optimization of a parking lot facility have been considered in research papers, there has not been much study conducted in the evacuation behavior of a parking lot in the event of an emergency. A smooth and steady evacuation of a parking lot is essential within evacuation plans, since the behaviors of evacuees in parking lots would be highly affected by the design and operation of the parking lot. Such factors as the number and locations of exits and the distance from the parking spot to the nearest exit are important components in determining the evacuation response rate.

To better evaluate the performance of a parking lot design, Yue and Yong (1996) employed a PC-based simulation package, PARKSIM2, to model the behaviors of pedestrians and vehicles in a parking lot. In particular, the model can be used to simulate the travel time and parking lot utilization. Multiple parking lot designs were presented and correspondingly the sensitivity analysis and validation of the designs were performed in terms of factors such as traffic flow, the number of parking spaces, O-D distribution, etc.

Van Der Waerden *et al.* (2002) presented a parking model named “Parking Analysis Model for Predicting Effects in Local Areas” (PAMELA), to investigate the effects of parking measures on the local areas, especially in commercial shopping areas. The model covers all aspects of a trip from when a motorist leaves his home to travel to a parking lot, to when the motorist exits the parking lot. PAMELA consists of several components such as the choice of destination and transport mode, parking lot familiarity, and the choice of parking lot and parking space. PAMELA uses an adaptive parking choice behavior model to handle the situation that a parking lot is fully occupied. The model simulates the behaviors of drivers’ choosing a parking space, such as keep searching in the same parking lot, parking illegally in the parking lot, or leaving to search for available parking spaces in another parking lot. PAMELA also considers the parking duration, which is the time taken for individuals to conduct activities. This time can have much influence on the behavior/operation of the whole parking lot.

Different from previous parking lot modeling, an agent-based model, PARKAGENT, was presented by Benenson *et al.* (2008). PARKAGENT can model the dynamic parking process of an individual driver in a real environment such as driving to parking lots, searching for parking spaces, and leaving the parking lot. PARKAGENT was built on GIS layers and is able to present real traffic infrastructures such as road attributes and parking lots. PARKAGENT operates in discrete time and space, and vehicles in the model can periodically update their state. The model uses shortest route assignment to model vehicle's route choice behaviors on an intersection. To apply varied agent behaviors rules to different groups of drivers, the parking process was separated into the following categories: driving towards the destination, searching for parking before reaching destination, searching for parking after passing the destination, and leaving the current parking lot. PARKAGENT also generates important distributions such as parking search time, walking distance to destination, and parking fees, in order to obtain the optimal parking place with the shortest time and distance and the least parking fee.

2.3. Microscopic Simulator Review

With the development of powerful computational resources, Agent-based modeling (ABM) also called individual based modeling (IBM), has emerged for modeling system characteristics by simulating the individual behavior of the entities called agents in the system. In ABM, an agent interacts with other agents and assesses its situation in order to make decisions according to preset rules. ABM has been widely applied because of its great capability in capturing the collective behavior of the system. A number of ABM simulators have been developed and applied in various fields, of which some applications have already been mentioned. This section focuses on reviewing the primary software tools available within this area.

TRANSIMS (Transportation Analysis and Simulation System), developed by Los Alamos National Laboratory, was initially designed for regional transportation planning and air forecasting analysis. The micro-simulator, integrating transportation planning models with advanced analysis models, can track the activity of various resources and the interactions between them second by second, including individuals, vehicles, and households, instead of aggregate traffic behavior. It employs shortest-time paths with dynamic feedback in route choice. Moreover, the TRANSIMS is an activity-based simulator with 2D and 3D representation of the networks.

As an agent-based micro-simulator, MATSim written in Java is able to simulate large-scale network traffic with millions of agents, including demand modeling, traffic flow simulation, and output analysis. It has been mainly developed by the Berlin Institute of Technology (TU Berlin) and the Swiss Federal Institute of Technology (ETH), providing detailed result analysis and network visualization enabling the modeling of the individual movement of the agents. With the ability of modeling time dependent networks, one of its applications is modeling evacuation scenarios. In addition, the hierarchical XML file format greatly facilitates the information exchange between modules. However, the presentation of simulation results is only available in a 2D format, which is much simplified and makes it hard to distinguish the variety of traffic modes (e.g. pedestrians, cars, trucks, and buses).

Created by MIT Intelligent Transportation Systems (ITS) Program, MITSIMLab was used to evaluate the traffic management system designs. Microscopic traffic simulator (MITSIM), as one of three primary modules with additional traffic management simulator (TMS) and graphical user interface (GUI), is used to track the movement of traffic flows. The driver behavior modeling is also embedded in MITSIM with a probability based route choice model.

As integrated multi-method simulation software, Anylogic is able to support various modeling on the basis of UML-RT and "Hybrid State charts", including ABM, system dynamics and discrete event modeling. For ABM, Anylogic enables the modeling of distinct activities such as agent movement, agent social networks formation, and agent communication. Written in Java, Anylogic can be operated in any platform and run on the web. Although it can be used in emergency planning and offers detail result analysis, Anylogic fails to differentiate the traffic modes and only provides for 2D animation.

The off-the-shelf micro-simulation packages include CORSIM, VISSIM, and PARAMICS in the U.S. CORSIM, developed by Federal Highway Administration (FHWA) consists of NETSIM and FRESIM, and is able to simulate the traffic in local arterials and freeways. It is based on Link-based routing without considering pedestrians; whereas VISSIM, developed by Planung Transport Verkehr (PTV), is Path-based routing. It can simulate multiple transport modes including pedestrian with 2D and 3D presentations of results. At present it has been used in more than 70 countries worldwide. Another is Q-PARAMICS developed by Quadstone Paramics. Paramics can be applied for the local arterials and regional freeway networks based on Link-based routing. It focuses on simulating the movements of people and individual vehicles, including the interaction between vehicles, and vehicles and pedestrians. It also involves the modeling of multiple transport modes with 3D presentation. (Choa, Milam & Stanek, 2003)

Based on the comparison among CORSIM, VISSIM and Paramics, Choa *et al.* (2003) concluded that the Paramics and VISSIM were better in simulating a specific traffic project. Krogscheepers and Kacir (2001) presented several application examples of Paramics indicating that the Paramics could perform well in simulating networks such as freeways, surface streets and dense networks. In addition, there are numerous examples where Paramics has successfully simulated traffic networks. (Chen *et al.*, 2006; Chen and Zhan, 2008; Chu *et.al.*,2003; Ozbay *et al.*, 2005; Satinnam *et al.*, 2005)

Our project aims to develop, analyze and evaluate the evacuation of a region when an emergency happens. The project therefore requires the following:

- Analysis of traffic networks in a small neighborhood with freeway, arterial road and intersections
- Multiple transportation modes, especially the tracking of the movements of individual vehicles and pedestrians, and their interaction during the evacuation process
- Behavior simulation involving mimicking different departure time and dynamic route selection
- Evaluation of simulation results including the identification of the bottleneck locations in terms of congestion, total evacuation time, average travel speed, and delays in the system
- Animation/3-D presentation of simulation results

Based on the information above, we selected Paramics for use in this project. There is no doubt that simulation packages cannot represent all aspects of the real environment seamlessly and some requirements, more or less, may be beyond the capability of the software. Fortunately, one of most important features of Paramics is that it allows the modeler to develop real traffic mechanisms without the constraint of a default model. They can embed new algorithms, such as car flowing, dynamic route choice, lane changing, and etc., into Paramics through the API (Application Programming Interface), which extends the capability of realistic modeling.

In the paper by Chu *et al.* (2003), a basic methodology concerning the API was presented to enhance Paramic's simulation ability in the fields of lane changing, signals control, collecting traffic information, etc. Moreover, Bartin *et al.* (2005) developed a model for a specific traffic circle and roundabouts by using the API of Paramics. In the paper, a binary probit model was employed and integrated with Paramics to model the driver behavior of gap acceptance/rejection in uncontrolled intersections. A trial and error method was used to estimate the O-D matrix in the model. The comparison of the results between the default Paramics and Paramics using the API demonstrated the effectiveness of using the API Paramics to capture the situation.

3. Methodologies

There are numerous methods available to model evacuation situations. This project explores evacuation dynamics via a simulation approach. In this section, we provide general modeling methodologies concerning traffic simulations, since evacuation modeling often involves traffic simulation. We then present specific methodologies for the evacuation simulations used in this research.

3.1. General Traffic Simulation Methodologies Overview

Traffic simulations are divided into three categories: macro-simulation, micro-simulation, and meso-simulation. Although it may vary for different simulation categories, a general traffic simulation modeling methodologies should include following steps as shown in **Figure 1**.

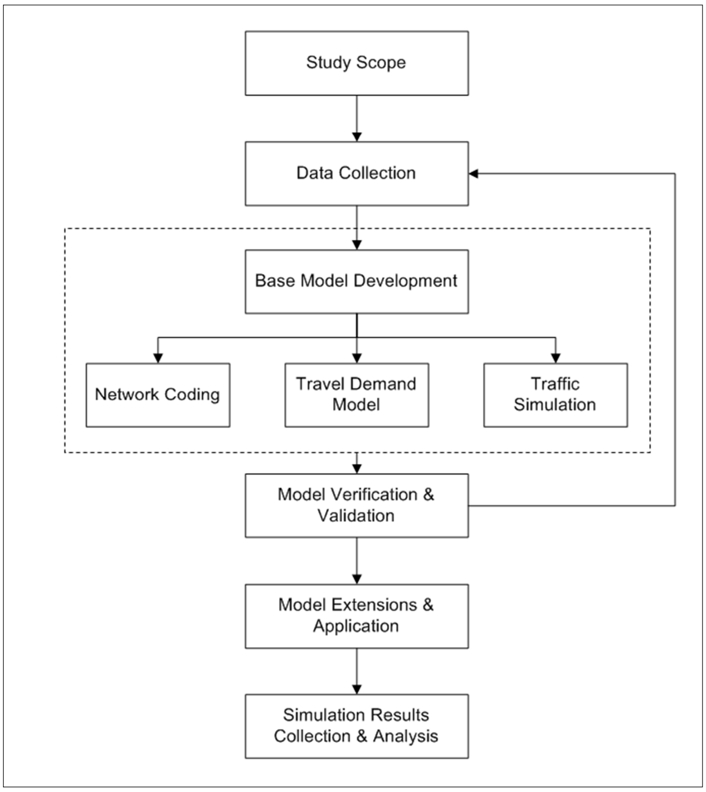


Figure 1. A diagram of General Traffic Simulation Modeling Methodologies

1) Study Scope

This step is to identify and define the problem. Since the simulation must perform experiments by making effort to model real environment, generally it is a time-consuming and resources-intensive process. Simulation requires an understanding of the problem such as the objectives of the study, simulation package selection, modeling approaches, study timelines, etc. Therefore it is critical and cost efficient to clarify the problem before detailed modeling is initiated. In addition, modelers have to make a tradeoff between model accuracy and cost. The more accuracy that a model requires, the more time and resources it takes to develop.

2) Data Collection

Traffic simulation involves the modeling of the movements on traffic networks of resources such as vehicles, pedestrians, responders, etc. The data required for building simulation models may depend on the simulation package used and the study scope for particular projects; however, in general data requirements include elements such as road geometry data, traffic control data, traffic demand data, and model calibration data. Most of these items can generally be obtained from local transportation agencies or emergency planning departments.

3) Base Model Development

This step is to build initial traffic simulation models to represent the real traffic situation within the simulation model. It includes three elements: traffic network coding, travel demand modeling, and traffic simulation modeling.

Traffic Network Coding

This step consists of three components: road construction, traffic simulation and transport mode choice. The traffic network within the study region of the evacuation can be constructed based on the road geometry data obtained in data collection. Traffic simulation concerns the operation of vehicles or pedestrians on the road. The transport mode choice focuses on what types of transport mode is used in traffic such as cars, trucks, pedestrians, etc.

Travel Demand Model

Travel demand modeling specifies the number of vehicles or people traveling in the study region. It generally is a time-dependent variable and is specific for each origination and destination pair. The modeling includes:

- OD demand – Specify demand from an origination to a destination. OD demand information can be obtained from existing OD demand data.
- Route assignment model – Focuses on how a driver makes decision to use routes in the simulation. Generally there are multiple route choice models available, such as myopic route choice, optimization-based route assignment, pre-defined route assignment, or shortest routes assignment.
- Traffic loading rate – Load the time-dependent traffic in simulation model. The load rate is either dynamic or static. For the dynamic, the loading rate varies at different times, since traffic flow on the network may be a function of time. For a static loading rate the traffic flow is deterministic and does not change with time.

Traffic simulation model

This model is used to track the movements of traffic such as vehicles and pedestrians. For example, the movements of vehicles on a road are determined by car following rules, lane changing rules, gap acceptance rules, and other environmental factors.

4) Model Verification and Validation

This step evaluates the effectiveness of the base model. Generally, within an initial model constructed in Paramics or other simulation software, numerous errors exist (e.g. traffic flows not representative of actual). Therefore modifications have to be made to get the model closer to reality. In addition, validation of the model can be performed by comparing the simulation results with the observed data obtain from data collection. A procedure to calibrate the model is shown in **Figure 2**.

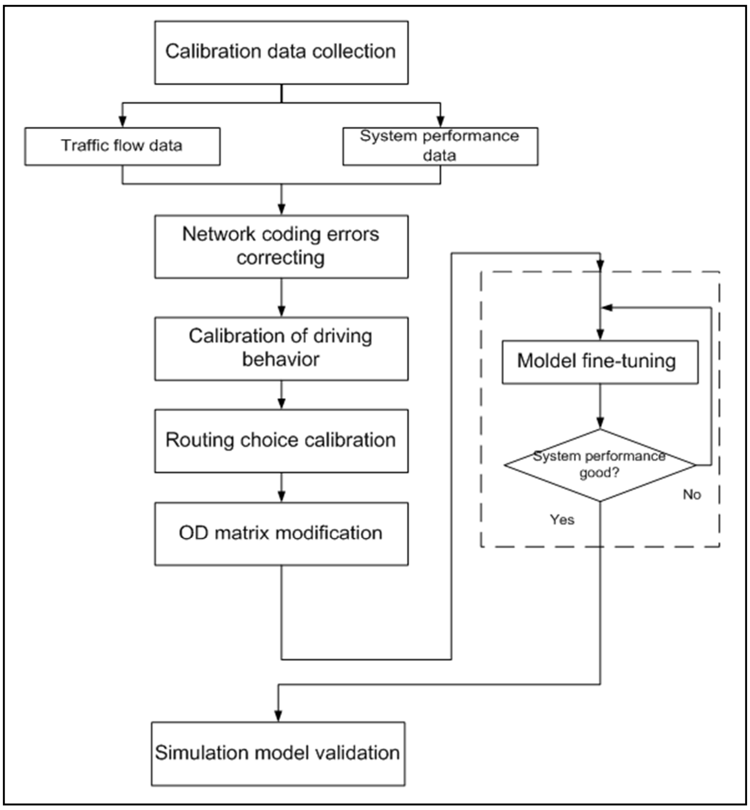


Figure 2. A diagram of Model Calibration

5) Model Extensions and Application

In this step, the model is used to simulate real scenarios. This may involve the development of additional models that are based upon the base model to include important modeling extensions (such as contra flow, etc.) In this step, multiple simulation runs are required to get statistically valid results.

6) Simulation Results Collection and Analysis

During the simulation model runs, the desired performance measures of effectiveness should be collected to analyze the model results.

3.2. Evacuation Simulation Methodologies Overview

Microscopic evacuations simulation has been investigated and applied in many research situations. This section presents a specific methodology for evacuation modeling as illustrated in **Figure 3.**

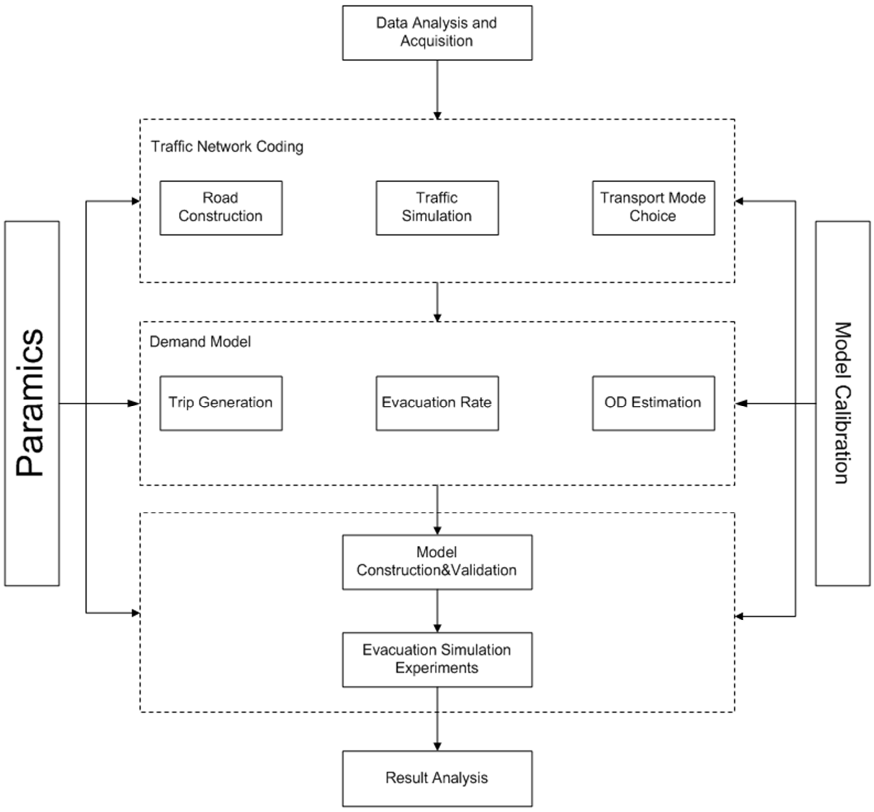


Figure 3. Schematic of Evacuation Simulation Methodology

1) Data Analysis and Acquisition

Within a defined scope of the project, it is critical to identify what data is necessary to construct the simulation model. The data required can be road geometry data, calibration data, traffic condition data, resources data of participating evacuation, etc. For example, road attribute data includes lengths and width, curves, speed limits. Without these data, the traffic network cannot be constructed. Generally these required data might be not obtained directly from local agencies.

2) Traffic Network Coding

In this project, Paramics was chosen as the simulator to build the simulation network. Paramics is able to input a variety of road data formats to construct road network such as GIS data and US Geological Survey digital orthophoto quads (DOQs). Furthermore, the initial traffic network built, Paramics allows detailed modifications of roads to represent the actual environment. Traffic speed limits have to be input and modified manually. In order to capture the behaviors of people and vehicles in the evacuation, it is necessary to simulate the real operation of traffic signals on the intersections. Multiple transport modes are considered in the project. For instance, evacuees may drive to escape or choose to evacuate on foot. In addition, vehicle types are different between evacuation traffic and background traffic in the affected region.

3) Trip Generation

Evacuation represents massive movements of resources such as vehicles and people. Therefore, the number of resources participating in the evacuation must be estimated in advance. Since the number of departing resources is variable at different times during the day, it is reasonable to develop a stochastic model to randomly generate the trip departure events. In this project we assume that the number of people that desire to evacuate is modeled by a Poisson distribution during the entire evacuation time, given the average number of vehicles for each trip origination.

4) Evacuation Rate Modeling

The concern in modeling the evacuation rate of evacuees is how to load resources onto the traffic network, which is different than typical traffic network modeling. In this step, we have to assign an evacuation beginning time to each evacuee. This process is also stochastic. Typically, logistic curves (S-curves) can provide a good representation to of this process, as indicated in the reviewed literature. We can also model the evacuation rate as a Poisson distribution, since the number of evacuees beginning to escape is low at the beginning of evacuation, increases gradually to a peak, then falls towards zero.

5) OD Estimation

In an evacuation, generally the origin can be a household, a parking space in a parking lot, or a building. The evacuation destinations can be safe zones or shelters located outside of the evacuation region. Generally, there are three methods used in previous studies. The simplest method is the shortest distance rule, where vehicles are assigned to the closest safe zones. Another is predetermined safe zones. In this situation, the evacuees will follow government plans to safe zones. In addition, probability assignment is also applied, where the probability for an evacuees' choice to a certain destination is based on considering integrated factors. (Cova and Johnson, 2002) The demand for each OD pair may be obtained from local transportation agencies.

6) Model Construction and Calibration

The traffic network automatically generated from Paramics contains errors in network geometry, road speed limits, traffic control settings, and other road attributes. First of all, network modifications can be made according to GIS data and online maps in order to make it closer to reality. For instance, intersections with multiple lanes and traffic speed limits have to be modified manually. Checking the animation results of the simulation model is also an efficient approach to eliminate minor errors. The default values of parameters in Paramics models may not be accurate enough to represent the real situation, and thus they can be calibrated with respect to the driving behavior model, the route choice model, and OD matrix estimation. For instance, we can change a driver's behavior by tuning values of the mean headway and driver reaction time.

7) Simulation Experiments and Results Analysis

In this step, multiple evacuation scenarios are developed to investigate the effectiveness of different evacuation strategies. For each scenario, we can vary factors such as the demand files, evacuation rate, traffic operations and destination choice. Because of the stochastic nature of the simulation, multiple replications are required. In the results analysis, the researchers generally take interest in both aggregate network performance metrics and disaggregate performance metrics. The former includes total evacuation time, average evacuation time, or average vehicle delay. The latter performance measures focus on results of individual evacuees such as vehicle evacuation travel times and vehicle evacuation delays from specific locations.

In order to demonstrate the concepts presented in this section, the next section presents a case study of the evacuation of the Northwest Arkansas Mall and the surrounding commercial shopping areas. We first describe the study region and the expected data collection activities involving demand analysis and data acquisition. Once the required data is identified, data resources and data sampling plans can be explored and developed respectively, in order to gather and prepare the data for use within the simulation model. Then key modeling issues are discussed such as trip generation, departure timing model, OD demand matrix, and parking lot modeling. A procedure for model calibration is also illustrated. The experimentation and results analysis are discussed via various evacuation scenarios. The spatial evacuation time distribution is a key performance metric of interest. Section 5 summarizes lessons learned from the research and areas open for future study.

4. A Case Study

To better address the evacuation methodologies presented in Section 3, we performed a case study of a large commercial shopping area. In this section, we start with a description of the study region to determine our study scope. We then provide a discussion on data identification and data acquisition. Also, more emphasis is placed on addressing simulation modeling issues. Finally, we develop evacuation scenarios and summarize the results from evacuation data analysis.

4.1. Study Region

Suppose there is a region where an emergency event (e.g. fire, terrorist attack, chemical dispersion, etc.) is detected to occur in a certain time. In such a scenario, all people (e.g. customers, staff, etc.) have to escape to safe areas within the surrounding area. In this project, the region around Northwest Arkansas Mall and Spring Creek Centre, which is within the red square shown in **Figure 4**, was selected as the emergency planning zone for a case study. The area is a highly visited shopping region with parking lots. Such an area offers a prime target for emergency events such as the release of a bio-chemical agent or a bomb attack by terrorists. The main local roads within the study region include US 71, East Joyce Boulevard, Main Drive, and East Zion Road. The project assumes that only mainline roads in the study area will be used for evacuation. This case study focuses on the process of how people evacuate to arrive at safe areas as long as the emergency takes place, and how the evacuation effects traffic flows. Building evacuation is not considered.

Figure 4. The Commercial Shopping Area under Study

4.2. Data Identification and Collection

Compared with other travel demand models, Paramics requires datasets having significantly more details for both simulation model construction and model evaluation. In this section, we start with descriptions of data needs. We then present a detailed description of how to perform data collection.

4.2.1. Data Identification

According to the scope of the project, the data required for building simulation networks in Paramics can be grouped into following categories:

- Simulation Network Coding Data – Provides descriptions of roads geometry, speed limits, parking lot layouts, traffic signals operations, and other environmental factors such as buildings or other facilities layouts.
- Traffic Operation Data – Provides general traffic characteristics such as traffic volumes, real traffic speeds, vehicle characteristics, driver behaviors, travel times, existing origination-destination matrices of background, etc.
- Demand Generation Data – Capture the state of resources including people and vehicles in the study region, such as the number or distribution of vehicles in parking lots or on roads.
- Model Calibration Data – Provides guidelines for verifying and validating simulation models, such as traffic counts, traffic volumes at observation stations, observed traffic speeds, traffic delays, etc.

A detailed discussion on each of these categories is provided as follows.

Simulation Network Coding Data

Network coding data primarily provides general information about the geometry of roads and traffic operation, from which a traffic network can be constructed. In general the network coding data includes: route geometry data, traffic signal operation data, and parking lot data.

1) Route Geometry Data

This data provides a general description of the characteristics of roads in the affected region including local arterials and highways. Generally, it consists of the following components:

- Lengths and Widths – Determine the extension and width of a road in two-dimension space. For example, N College Ave cuts through the study region from North to South. In addition, roads that can be divided into several small road segments must be noted. In addition, the speed limits may be different for the road segments along a road.
- Lanes – Include the number of lanes, lane width, lane increments and decrements, contra-flow lanes, lane usage on the roads and intersections. For example, for the intersection of N Mall Ave and E Joyce Blvd, there are three lanes along E Joyce Blvd from East to West: one left turn lane and two direct flow lanes.
- Curvature – Captures the drivers' behavior during turning movements and gradients. For example, a driver tends to reduce speed and adjust driver behavior on a vertical curvature. (e.g., there is a vertical curvature along the N College Ave)
- Road Priority – Sets the priority of the right of way on the non-signaling intersections. It is important to modify the road priority in the parking lots to allow traffic flows to properly operate.
- Free flow speed – Presents the maximum speed of a driver without conflicting traffic flows. In the project, speed limits of the road segments were used to represent the traffic speed.

2) Traffic Signal Operation Data

This data is used to control traffic flow, which represents the normal traffic operation situation without evacuation traffic. For completely capturing the traffic control characteristics, the following information is required:

- The location and the number of traffic signals – Determine the locations of traffic signals in the study region, especially on the key intersections. (e.g., the intersection of N College Ave and E Joyce Blvd)
- Signal Cycle Timing Plans – Describe the operating patterns of the traffic signals. A cycle of a traffic signal includes several phases during which green lights, yellow lights, and red lights operate iteratively. Generally, traffic signals can be divided into two categories. One is the fixed timing signals; the other is based on flexible timing plans, that is, sensor lights. Therefore, it is important to identify the type of signals and their operational patterns. This information can be provided by local transportation departments. For instance, there is a sensor signal on the intersection of E Joyce Blvd and Steele Blvd.

3) Parking Lot Data

This data provides descriptions of parking lots in the study region. The origin of evacuation traffic is assumed to be within parking lots. Therefore, information on parking lots such as the number and design of individual parking spaces, traffic flow directions in parking lots, speed limits, and the number of exits and entrances is required. For example, there are about thirteen parking rows with 800 individual parking spaces at the Wal-Mart store within the study region. The speed limit is observed to be about 10 mile per hour with bi-directional traffic.

Traffic Operation Data

Traffic operation data provides basic information about the traffic situations and states. This data is primarily used to construct the traffic simulation model. Typically, traffic performance data such as traffic speed, travel time, and traffic volume can be obtained from numerous data resources. For existing OD matrices of background traffic, local travel demand sources may be available; however, the data may have to be modified because traffic modeling is different when evacuations occur. Traffic operation data primarily includes: vehicle characteristics and origin/destination matrices,

1) Vehicle Characteristics

In the project, vehicles are the main transport mode without considering effects from pedestrians. In general, vehicles characteristics include the following elements:

- Vehicle Mixture by Type Data

Vehicle mixture by type data includes the information about vehicle types and their percentages. Different vehicle types may have varied attributes and performance such as the acceleration rate and the gap acceptance for changing lanes. Different combinations of vehicle types may also affect the behavior of traffic flow on the whole. According to observations within the study region, the vehicle mix types can be grouped into two categories by locations: the vehicle types in the parking lots and vehicle types on the roads. Generally the type of vehicles moving on the mainline roads is varied such as trucks, buses, cars, etc, whereas the type of vehicles is limited within the parking lots. For example, it is unusual to have large trucks moving within parking lots of a shopping area. During evacuation, the former vehicle types are used in evacuation traffic, and the latter in background traffic.

- Vehicles Attributes Data

This data describes the outline of vehicles such as length, height and width. Based on the data, road usage for specific vehicles can be specified. For example, specific vehicles may not be allowed to use a road in some circumstances such as emergencies.

- Vehicle Performance Data

This data provides kinematical information of vehicles such as acceleration rate, maximum deceleration rate, maximum speed, and maximum rate of change in acceleration rates, which also affects evacuation time.

2) Existing OD Demand Matrices

The existing OD matrices are used to model background traffic without evacuation. An OD demand matrix represents the number of trips from an origin to a destination. Since the data concerning the OD demand matrix of the background traffic is limited, the OD matrices were built manually based on observed traffic counts. Typically, this can be accomplished by distributing traffic volumes in two aspects: traffic volumes entering the study area and intersection turning volumes. Specifically, only peak periods in the afternoon are selected for the simulation modeling in the project. In addition, only mainline roads will be used in the simulation network construction; therefore, the existing traffic flows can be reduced to several roads within specific time periods.

Demand Generation Data

Demand generation data provides the information of resources participating in the evacuation. In micro-simulation modeling, demand generation is one of the most important steps, since it determines the number of evacuees during an evacuation which will, in turn, affect the evacuation performance. Generally, the demand data includes the distribution of vehicles and pedestrians as follows:

1) Vehicle Distribution Data

Based on the previous discussion, the origins of trips include parking lots and locations on the roads. For demand generation, the vehicle distribution within each parking lot and during study time periods is of importance. For example, the occupancy rate of a parking lot is required to estimate the number of vehicles to be generated.

2) Pedestrians distribution

There are lots of shoppers and pedestrians within a study area, such as Northwest Arkansas Mall and Spring Creek Centre. During the evacuation, the customers will desire to evacuate as soon as possible. Therefore, the number and distribution of the pedestrians and shoppers should be estimated in order to simulate the friction between vehicles and pedestrians during peak hours and off-peak hours respectively. In this project, transport modes are constricted to be vehicles, not considering the interaction from pedestrians. Pedestrians will be considered in future work.

Model Calibration Data

Calibration data is observation data from the real environment. Based on the comparison between simulation results and calibration data, basic simulation models can be modified to represent reality. Calibration data primarily includes two groups of data: traffic flow data and traffic system performance data. The traffic flow data is the same with the traffic operation data such as traffic capacity, traffic volumes, pedestrian data, etc. This data is used to construct and validate the background traffic simulation model. The system performance data includes travel time, delay, queues on freeways and arterials. In this project, traffic counts at pre-defined observation stations are used to calibrate the model. The specific data survey was performed during afternoon peak hours on typical weekdays.

4.2.2. Data Acquisition

Given the massive data requirements as discussed in the prior section, it is important to collect data more efficiently in order to save time and resources. Based on the search of local data resources, these data are sometimes available from numerous agencies. Unfortunately, there are only few data sources that were available for this specific study area. Therefore, we performed some data collection manually to obtain the data for park lots and traffic volumes. In this section, we first introduce some data resources to use, and then provide a general discussion on the data survey process.

Data Resources

There are lots of local agencies that may be helpful during the data collection phase of a project. Some of the sources for this project included:.

- The Arkansas State Highway and Transportation Department
- City of Fayetteville Transportation Division
- Northwest Arkansas Regional Planning
- The Center for Advanced Spatial Technologies

During the project, we primarily used the data from CAST (Center for Advanced Spatial Technologies) at the University of Arkansas. The data played an important role in constructing the simulation traffic network, and provided part of the information concerning traffic operation situation such as travel time. However, additional data needed to be collected.

Data Survey Process

Given the scarcity of data it was necessary to manually collect parking lot data, traffic signal operation data, and traffic count data. The data collect process was addressed generally as follows.

1) Parking Lot Data Survey

Because data concerning the distribution of vehicles in the study region was unavailable, a data sampling plan was developed for parking lots. Generally, a parking lot can be simply described as in **Figure 5**. Each parking row can be partitioned into three aggregate parking zones. One is the nearest to the exit of the store. The second is the closer to the exit. The middle of the parking lot constitutes the remaining part of the parking lot. In the project, we model the origin of evacuation traffic by aggregated parking zones, not individual parking spaces. In order to build an OD demand matrix, we have to obtain the distribution of vehicles for each parking zone both in different times of the day and in different days of the week. Since our studied evacuation time is afternoon peaking hours, the time to collect the vehicle distribution is shown in **Table 1**.

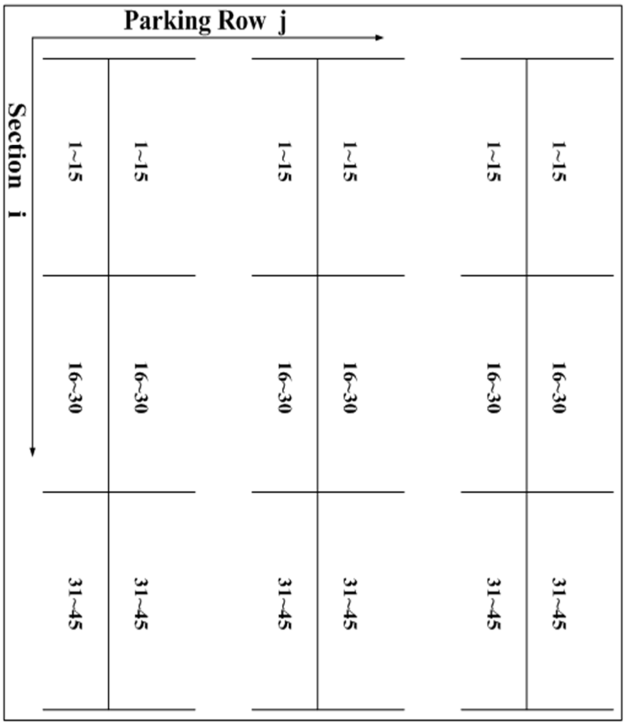


Figure 5. Simplified Layout of Parking Lot

Table 1. Sampling Time Schedule

Cars Numbers (N(t))								
		Mon	Tue	Wed	Thu	Fri	Sat	Sun
Afternoon	4:00 pm							
	5:00 pm							
	6:00 pm							
	7:00 pm							

Considering the complexity and time consuming nature of on-site data collection, it is not realistic to collect the data for each individual parking zone. Therefore we developed a simplified approach as follows. (An alternative survey method of individual parking zones is described in Appendix A1.)

Let N_j be the total number of parking spaces in parking lot j, and n_{jtd} be the number of vehicles parking at parking lot j at time point t of a day d in a week, where t is from 4 pm to 7 pm, d from Mon to Sun.

- Count n_{jtd} for each parking lot

This step will not be concerned with the location of vehicles, but instead estimate the total number of vehicles in each parking lot at different time points.

- Calculate the occupancy rate R_{jtd}, that is, the proportion of the number of vehicles to the total number of parking spaces in parking lot j at the time t of day d in a week.

$$R_{jtd} = \frac{n_{jtd}}{N_j}, \qquad j\epsilon 1, \dots, J, \qquad t\epsilon 4, \dots 7, \qquad d\epsilon 1, \dots, 7$$

Based on the data sampling, the occupancy rate of vehicles for each parking lot from 4 pm to 7 pm is different, whereas the occupancy rate is similar for each parking lot at the same time during a week. The observed occupancy rates for each parking lot are shown in **Figure 6**. Generally, the occupancy rate on the weekend is larger than on Monday through Friday. In this project, we only consider the worst case with the maximal occupancy rate for each parking lot for a day through a week.

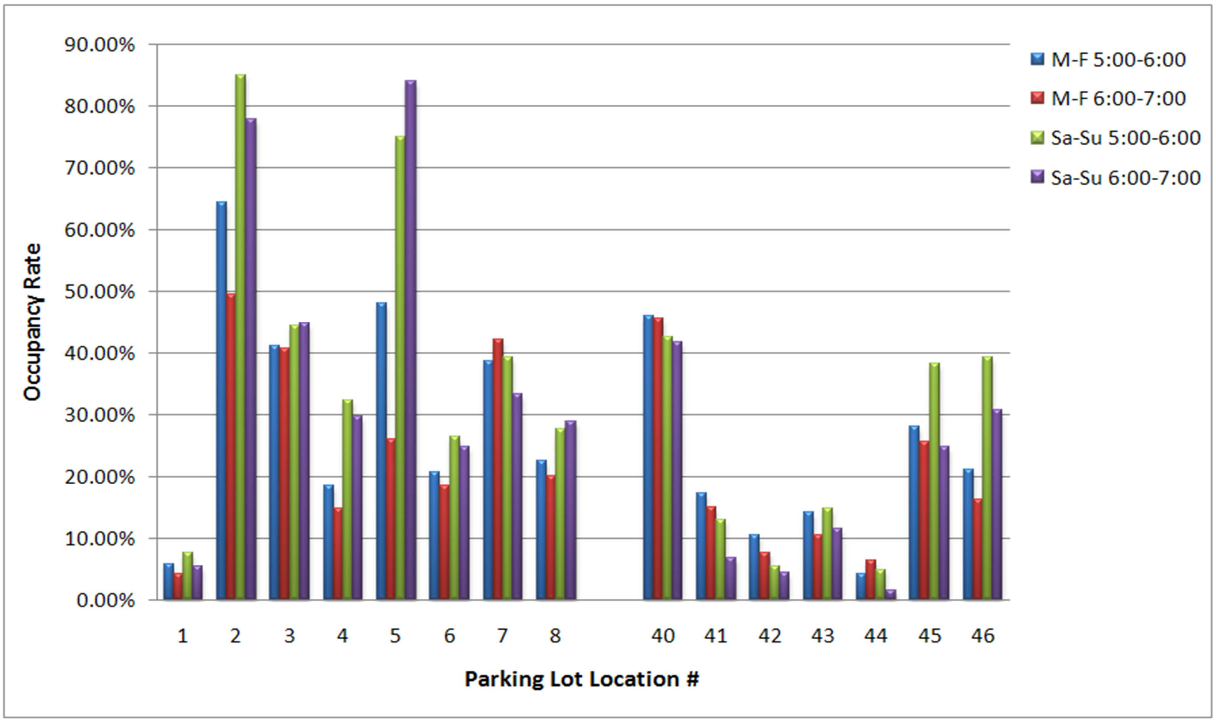


Figure 6. Occupancy Rates of Parking Lots

2) Traffic Volume Survey

The traffic volumes from sources at important locations are only available for peak hours and off-peak hours. For example, there are two peak hours in data obtained from CAST: AM peaking hours from 6:00 am to 9:00 am and PM peak hours from 3:00 pm to 6:00 pm. The rest of the time is off-peak hours. Therefore, traffic volumes from CAST are only available for these three time periods and we cannot get hourly traffic volumes during our period of interest. In the modeling building process, however, we need more detailed data, such as traffic volumes for every hour on each road segment. Therefore, nine key observation stations were selected as representative of the entire simulation network to count traffic volumes as shown in **Figure 7**. The selection of these 9 observation stations was designed to collect traffic counts in both traffic directions with 15 minutes time interval during time period 16:30pm to 17:30 at each observation station. The initial observed traffic counts at each location are shown in **Table 2**.

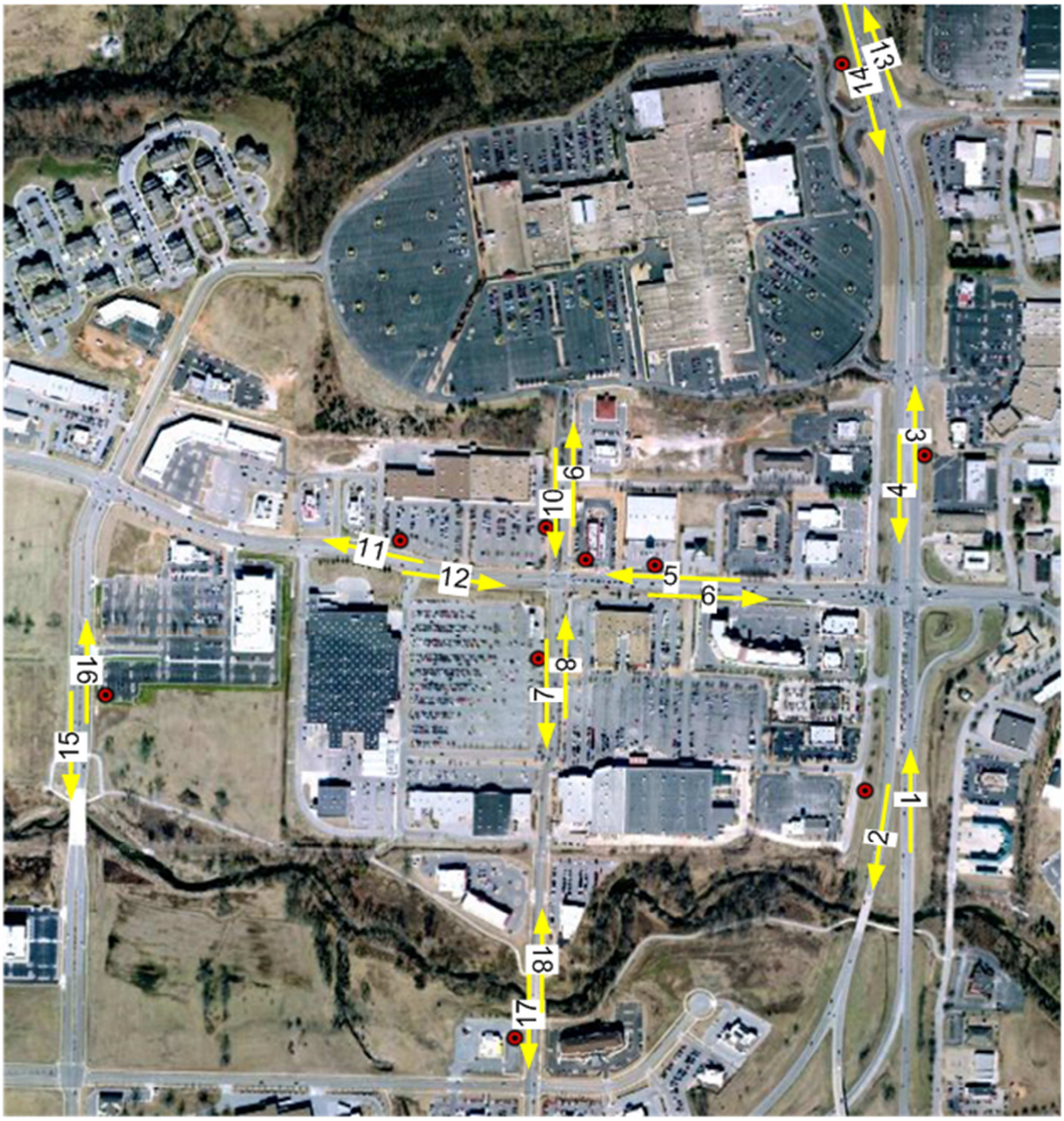


Figure 7. Data Observation Stations

Table 2. Observed Traffic Counts at Observation Stations

Obs Loc	16:30-16:45	16:45-17:00	17:00-17:15	17:15-17:30	Subtot
1	464	490	380	355	1689
2	415	425	340	320	1500
3	372	451	490	410	1723
4	365	395	425	366	1551
5	317	319	331	326	1293
6	205	205	239	250	899
7	164	163	143	143	613
8	94	104	117	103	418
9	110	103	104	100	417
10	87	79	78	68	312
11	177	210	204	226	817
12	170	183	163	181	697
13	264	260	277	197	998
14	309	259	286	266	1120
15	54	54	54	54	216
16	49	49	49	49	196

3) Traffic Signal Survey

According to the road network within the study region, traffic signals are located on five intersections shown with green circles in **Figure 8**. Therefore five traffic signals are necessary to handle traffic conditions in the simulation model. For example, the traffic signal timing plan for the intersection of E Joyce Blvd and N College Ave, that is the intersection 3, is required. Generally, there may be several phases within a cycle of the traffic light control. Within each phase, the direction of the traffic flow is different, which is controlled by red, yellow, and green signals. As a result, the traffic flow arrows and times of signals (red, green, and yellow) are required for specifying the operation of an intersection. As shown in **Figure 9**, there are 5 phases and only major directions of traffic flow are shown. The analysis does not represent traffic flows; however, those will be considered within the simulation models. In addition, the traffic signal timing plan will be modified corresponding to its location. Because some roads do not allow inward traffic flows during evacuation, these roads will be barred and the corresponding traffic signal will be cancelled. Since traffic signal 5 is a sensor based light, we cannot capture its cycle time. In this research, we define its cycle time the same as the cycle time for traffic signal 4. (The traffic signal plans for other locations are in Appendix A).

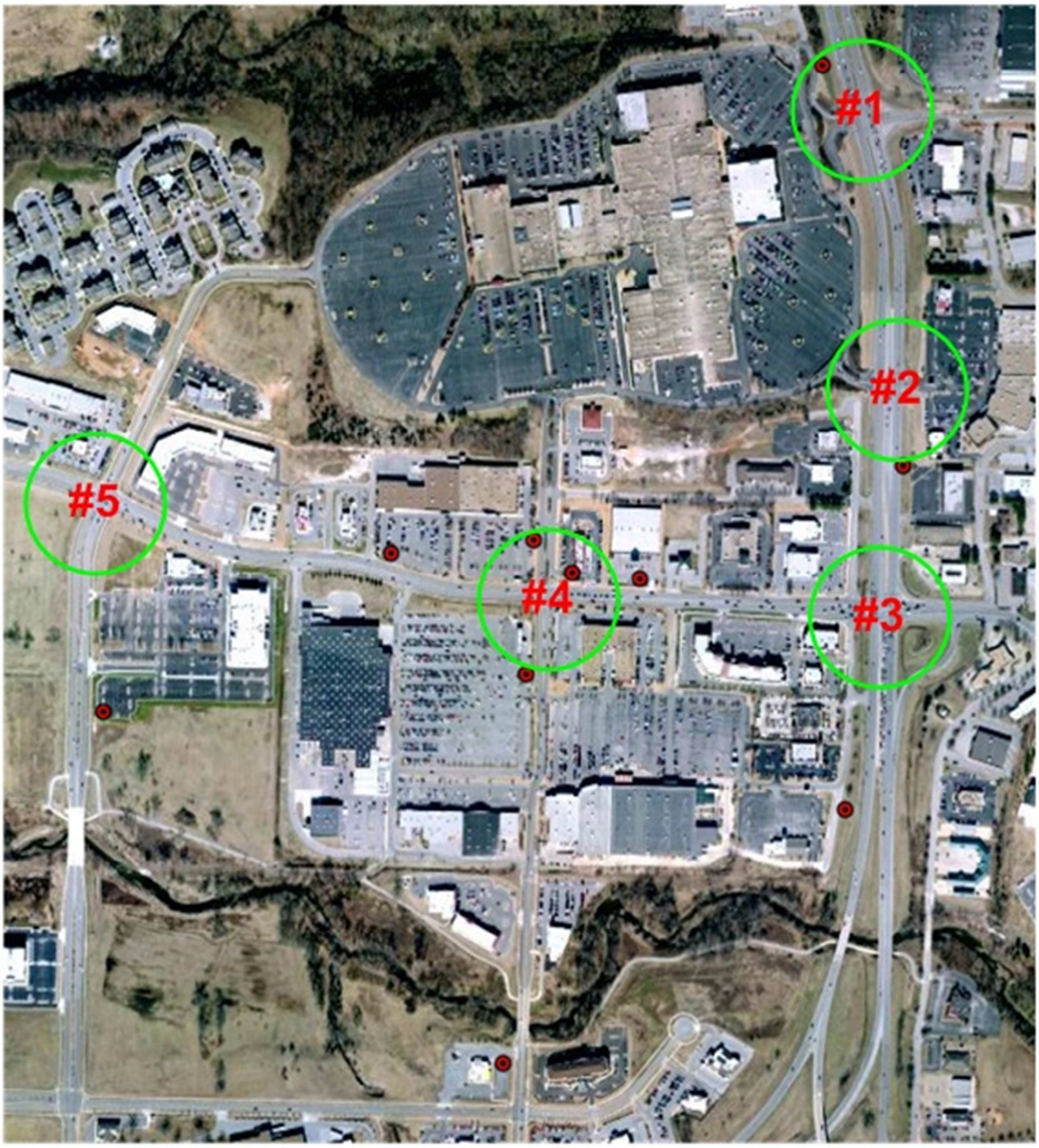
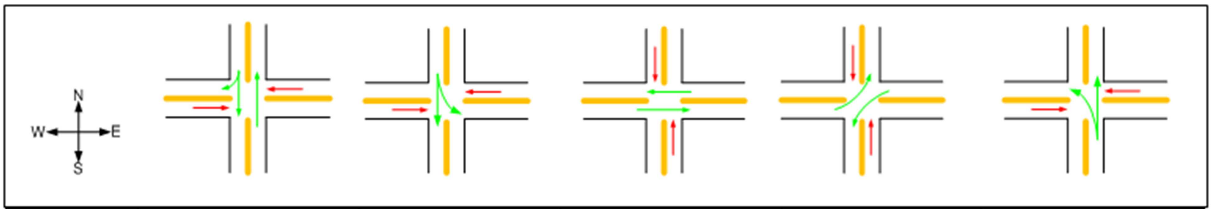


Figure 8. Locations of Traffic Signals



	Phase 1			Phase 2			phase 3			Phase 4			Phase 5		
	R	G	Y	R	G	Y	R	G	Y	R	G	Y	R	G	Y
	1.27	18.39	2.91	2	13.77	4.31	1.13	18.45	2.44	1	18.91	3.5	2.16	22.46	3.34
	1.92	21.91	2.13	2	13.47	3.4	1	18.51	3.27	1	18.72	2.97	2.42	22.96	3.27
	1.39	18.16	2.98	2	14.59	4.46	1.28	19.81	3.12	1	18.72	3.7	2.21	22.87	3.33
	1.22	18.2	3.64	2	14.43	4.53	2.08	19.71	3.86	1	18.39	3.83	2.02	22.98	3.46
	1.18	18.31	3.61	2			2.09	18.44	3.77		18.92	3.91	2.11	22.79	3.39
	1.17	18.27		2			2.09		3.5				2.39		3.44
Average	**1**	**19**	**3**	**2**	**14**	**4**	**2**	**19**	**3**	**1**	**19**	**4**	**2**	**23**	**3**

Figure 9. Traffic Signal Timing Plan on Intersection of E Joyce Blvd & N College Ave (3)

4.3. Background Traffic Model Construction

Since Paramics has been selected, this section starts with the discussion of the key modeling issues for simulation model building, and then briefly introduces some techniques in model calibration based on the use of Paramics. A background traffic simulation model without considering evacuation traffic flow is established and model validation is presented.

4.3.1. Key Modeling Issues

Parking Lot Modeling

Under an emergency situation, people will be desperate to leave the building, walk to their vehicles, and drive out of the parking lot into the traffic network. This process will involve the movements of vehicles and pedestrians as well as their friction. Emphasizing the movements of resources (e.g. buses, trucks, cars, and pedestrians) and their interactions during the evacuation scenarios, this project emphasizes parking lots as the demand origination points in order to reflect the real traffic flows during the evacuation.

Generally, in Paramics, a node represents an intersection, a link represents a road, and a zone built on a link can release vehicles onto the network shown in **Figure 10**. Area zones can be used to represent residential areas, parking lots, parking rows etc. (Qudstone Paramics Ltd, 2009)

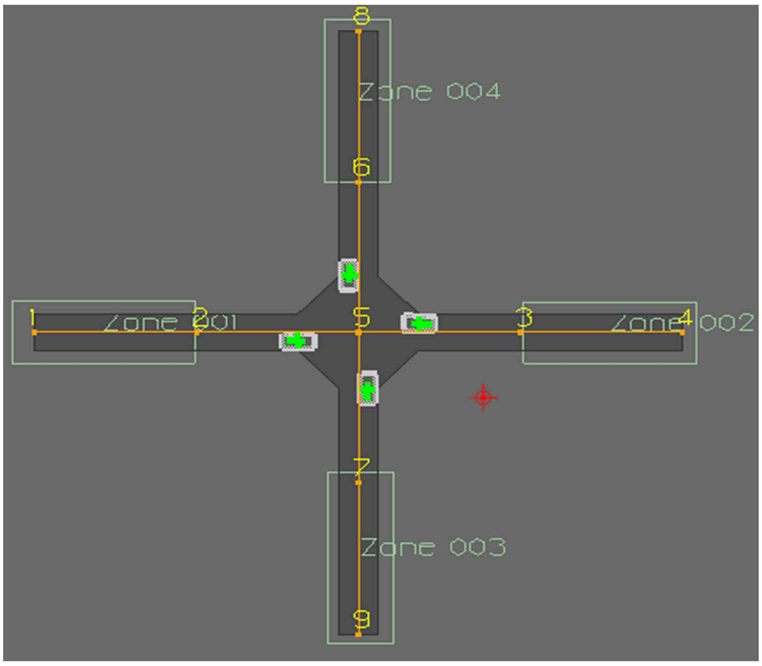


Figure 10. Network Coding in Paramics

Based on the observation of parking lots, it is obvious that parking spaces are close to each other. In addition, an individual parking space is generally less than 6 m in length and 3m in width. However, Paramics requires that the minimum length of a link must be 20m in order to build zones for generating demands, and it appears to be impossible to build two links with 0 distances next to each other for simulating individual parking spaces. These restrictions in the physical modeling capabilities of Paramics prevent it from modeling individual parking spaces an origin zones. Thus, we decided to approximately modeling a parking lot by aggregating each parking row into several sections. Since the project aims at analyzing and evaluating the evacuation plan over a region when an emergency happens, this approach simplifies the detail within the simulation.

In the approach, each parking row will be separated into zones of about 20m. Typically, there are three zones in each parking lot: the closet to the entrance of the building (parking row 1), the farthest (parking row 3), and the middle between the two outer zones (parking row 2). For example, as shown in **Figure 11**, the parking spaces from 1 to 15 are in parking row 1, from 16 to 30 in parking row 2, and the rest are in parking row 3. In this method, the vehicles are aggregated into each zone, and we only focus on the collective behavior of each zone, ignoring the details of vehicle movements contained in each zone.

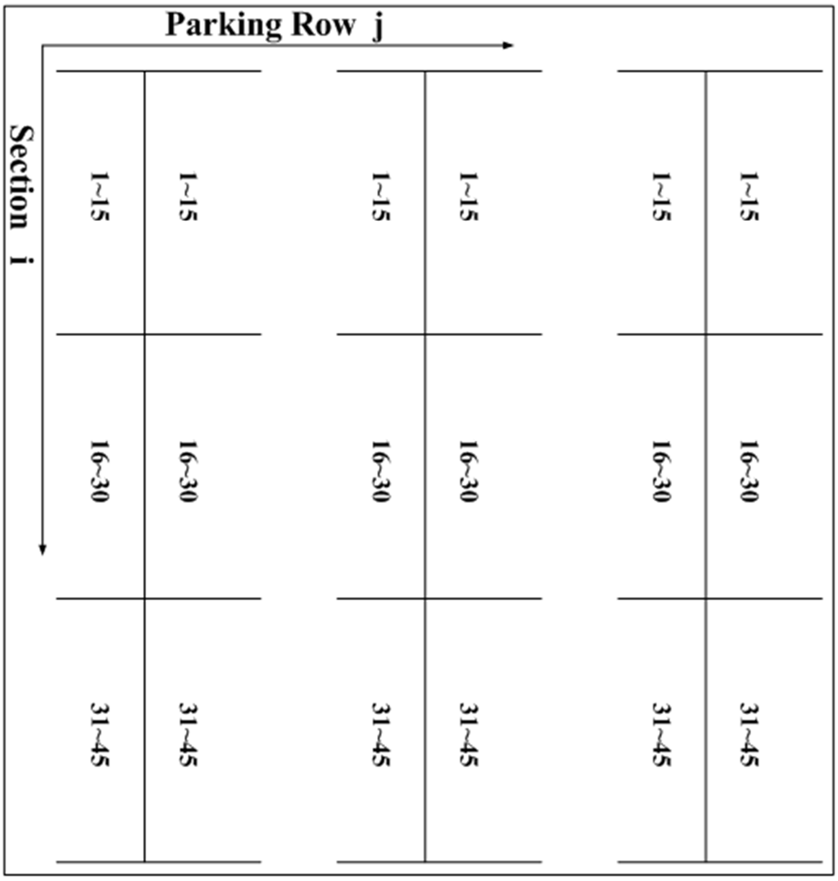


Figure 11. Aggregate layout of the parking lot

Demand Generation in Paramics

There are several files used to construct simulation models in Paramics. These files are briefly introduced in this section.

1) Demand File

This file specifies the number of vehicles to travel from each origin zone to each destination zone. We can define a demand file by vehicle type and demand period as shown in **Figure 12**. For example, there are two types of vehicles in the case study, and two demand periods from 4:30 pm to 5:30 pm and from 5:30 pm to 8:30 pm. Therefore, two demand files are required to represent background traffic and evacuation traffic during each period.

Matrix Count: 2 Demand Period: 1 Divisor: 1.00 Current Matrix: 1 Vehicle Type:

	Zone 2	Zone 3	Zone 4	Total
Zone 2		20	20	40
Zone 3	20		20	40
Zone 4	20	20		40
Total	40	40	40	120

Figure 12. Demand Files in Paramics

2) Profile File

Profile files specify a more precise traffic release rate, by dividing the simulation time into small slices. Since the evacuation rate is stochastic and varied by time, Paramics requires percentage input during each time slice with all total sums equal to one. For example, evacuation rates are 40%, 30%, and 30% respectively for period 1 in **Figure 13**, given the time interval is 15 minutes for period 1.

Profile Count: 1 Period Count: 2 Interval: 20 Current Profile: 1 Divisor: 1.00

	Start Time				Total
Period 1	06:00:00	40	30	30	100
Period 2	07:00:00	40	30	30	100

Figure 13. Profile Files in Paramics

3) Matrix File

The Matrix file specifies the percentage of vehicles by type released for a given origin and destination pair. For this case study, there are two types of vehicles. As a result, two matrices: 1 and 2 are created in Paramics corresponding to each vehicle combination. By assigning the matrix number to each OD pair, we can define the percentage of vehicles operating in the OD pair shown in **Figure 14.** In this research, these files are generated using Java programming.

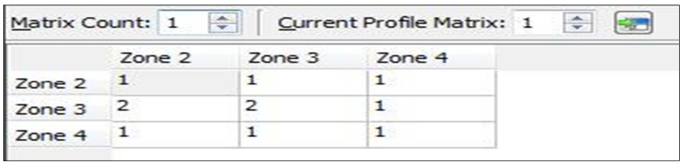


Figure 14. Matrix Files in Paramics

4.3.2. Base Model Construction

The base model is an initial simulation model with background traffic which involves normal traffic such as peak-hour traffic and shoppers. The objective of the base model is to represent the evacuation traffic network and simulate background traffic condition at the beginning of an evacuation. Then, it is possible to model the interaction between evacuation traffic flow and background traffic flow on the roads. In addition, the base model can be used to assist with the validation of the simulation model by comparing the simulation results with observed data.

Basic Assumptions

1) Only major roads in the affected region will be used as evacuation routes. Background traffic flow is constrained to the main predefined roads and is not allowed to use routes involving smaller roads.

In an evacuation situation, it is highly possible that most of the evacuees will select major roads to escape rather than minor roads, and hence it may not be necessary to model the traffic flow involving minor road routes. In the case study, traffic flows on the road N College Ave, E Joyce Blvd, and N Mall Ave are selected to be representative background traffic flow in the model. Vehicles on these roads will not choose roads entering parking lots.

2) Background traffic flow on the main roads of the simulation network can be represented by observed traffic flows at the survey locations.

The traffic volume observed at a survey station is assumed to be equivalent to traffic volume at that road segment, without considering the difference of traffic volume inside the road. Only a few turning movements are allowed on some intersections to balance traffic volumes on different roads. For instance, suppose that there are three road segments illustrated in **Figure 15** on North College Ave: segment #1, segment #2, and segment #3, among which traffic volumes are different among each small road segment. In the case study, we assume traffic volumes beyond the north entrance of Mall (segment #1) can be represented by traffic volumes at number 13 and 14. Similarly, traffic volumes at 3 and 4 are for road segment #2 between the north entrance and south entrance of the mall. Finally, 1 and 2 are used for the traffic volumes for road segment #3 beyond the intersection of N College Ave and E Joyce Blvd.

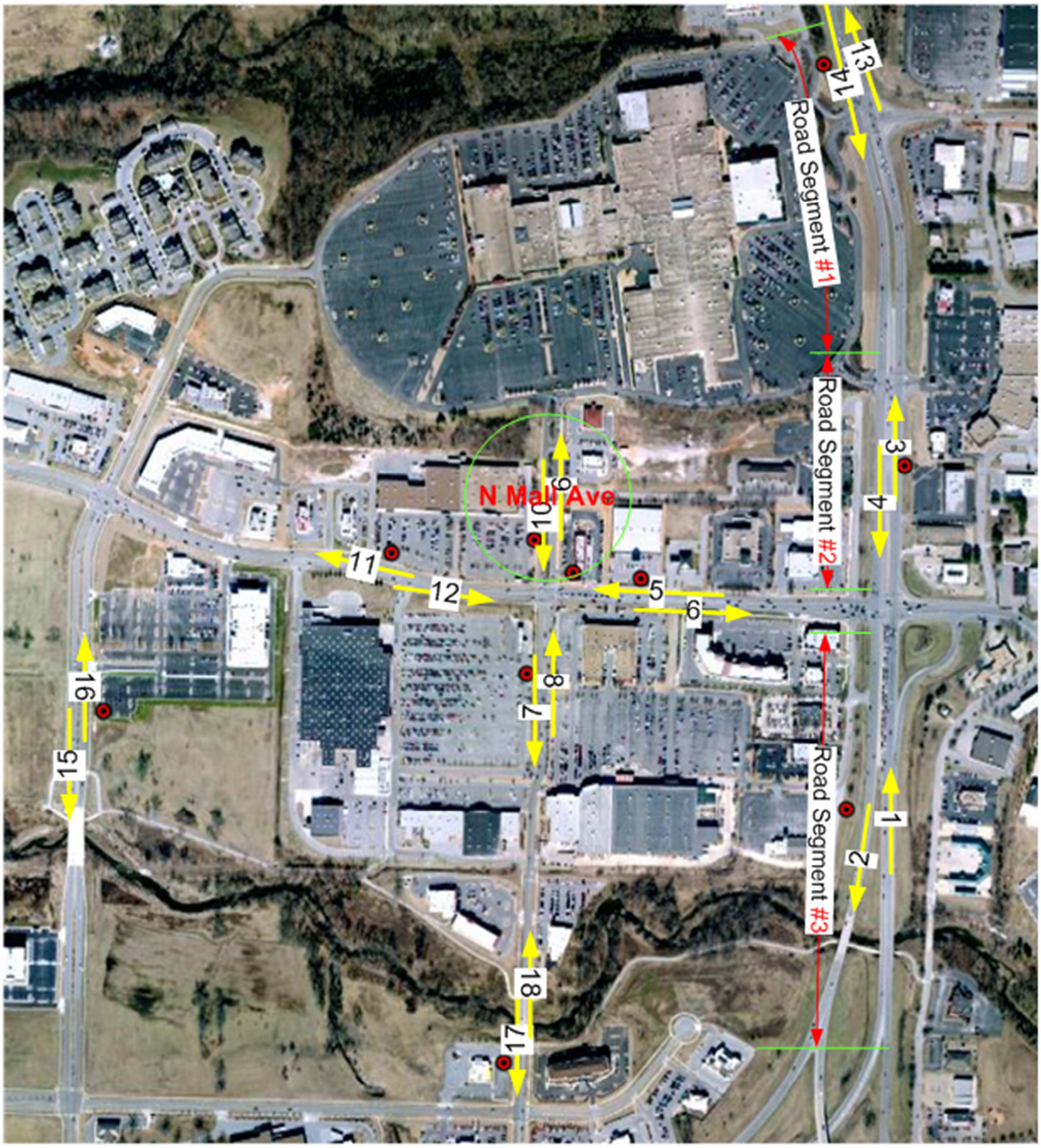


Figure 15. Representative traffic flows

3) No vehicle drives into parking lots, and hence traffic flows from main roads to parking lots will be barred, and traffic signal timing plans will be adjusted accordingly.

For instance, N Mall Ave within the green circle in **Figure 15** will be closed for vehicles entering parking lots. This forces vehicles to be only able to driving out of parking lots. This is reasonable because most drivers will desire to escape out of parking lots (once an evacuation begins), and drivers from background traffic will change their routines once they notice the emergency. The resulting traffic flows will be distributed onto other roads.

4) Default vehicle type mix is used for the background traffic flow.

5) No perturbation factor will be considered. Driver familiarity is assumed to be 100%.

The factors of perturbation and familiarity are used to control route assignments in Paramics. The higher the perturbation factor value is, the more route choices are available for a vehicle at an intersection. If perturbation is 0, this means that the vehicle will follow a pre-defined route and this route will not be updated periodically. Generally, a driver may decide to take a shorter route at an intersection if he notices the current route will take additional time to get to the destination. In the base model, drivers are not allowed to randomly change routes at intersections. The background traffic is predefined to model traffic patterns on main roads and all drivers are assumed to be familiar with the roads.

6) Mean target time and mean reaction time is 0.62s and 0.41s respectively.

Mean target time and mean reaction time are used in route assignment algorithms, therefore their value will to some extent affect the simulation results once the evacuation traffic is loaded. Due to the scarcity of relevant data, we assume these values are known as 0.62s and 0.41s respectively.

7) Traffic signals at intersections take fixed timing plans, without considering variable timing plans (e.g. sensor lights).

In the study region, the diversity of traffic signal timing plans imposes another challenge. For instance, it is difficult to capture signal plans if the traffic lights are senor based, where signal time is highly dependent on the length of queue on each lane. Without an external programming package such as Programmer, Paramics cannot model this situation. For simplicity, the project assumes that all the traffic lights are fixed timing lights.

8) Two way left turn lanes (TWLTLs), called suicide lanes or chicken lanes are not built in the base model.

Network Coding

The simulation traffic network of the study region can be built using Converter in Paramics. Converter can extract network data from several data sources (e.g. emme/2, ESRI Shape Files, MapInfo, Corsim, CSV, etc.) and convert it into a basic simulation network applicable in Paramics. For the case study, ESRI shapes files from CAST were used as the data source to generate the road network.

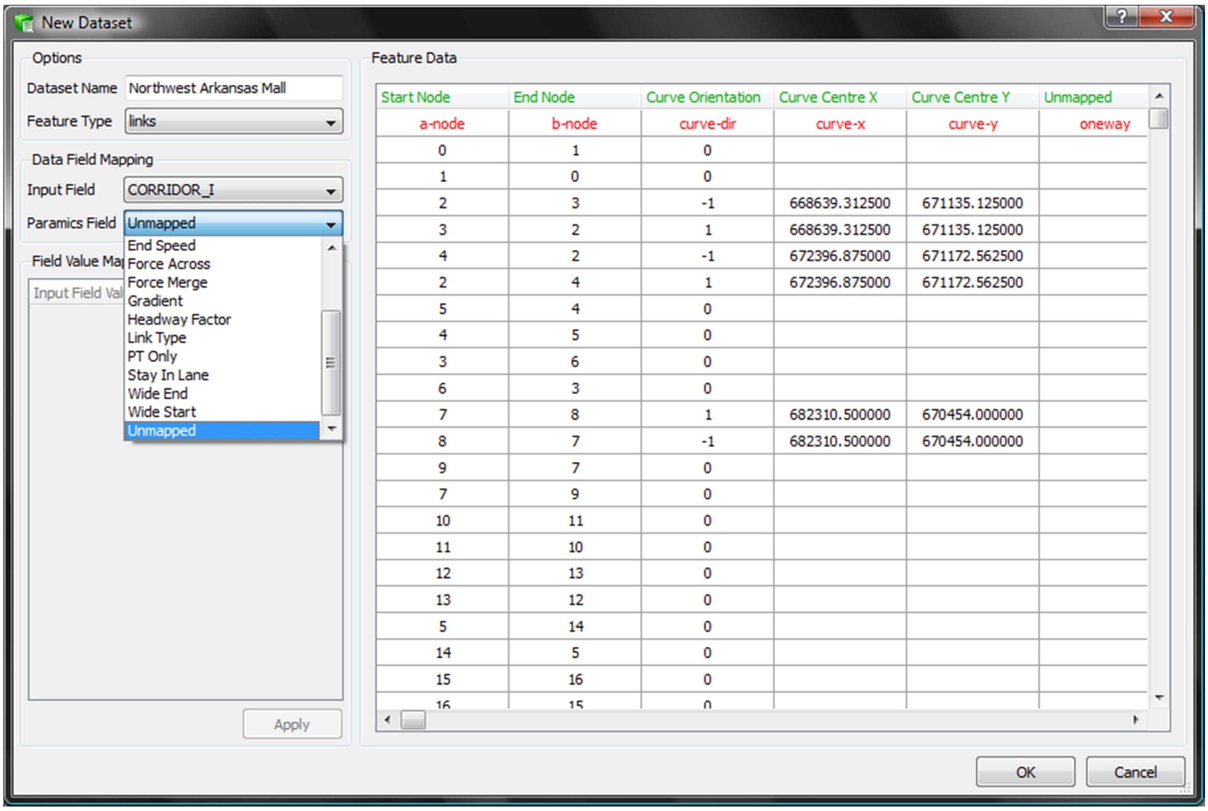


Figure 16. Dataset in Converter

As shown in **Figure 16**, Converter requires users to select input data manually and there are several key parameters for a road (link in Paramics) listed as follows:

- Starting node
- Ending node
- One way
- Number of lanes
- Lane width
- Road speed (free flow speed, not speed limit)

Generally, the initial network transformed from Converter contains numerous errors, and hence modification of road attributes has to be performed before using the network. These modifications include: number of lanes at intersections, intersection signal plans, lane width, lane length, free flow speed, road vertical height, etc.

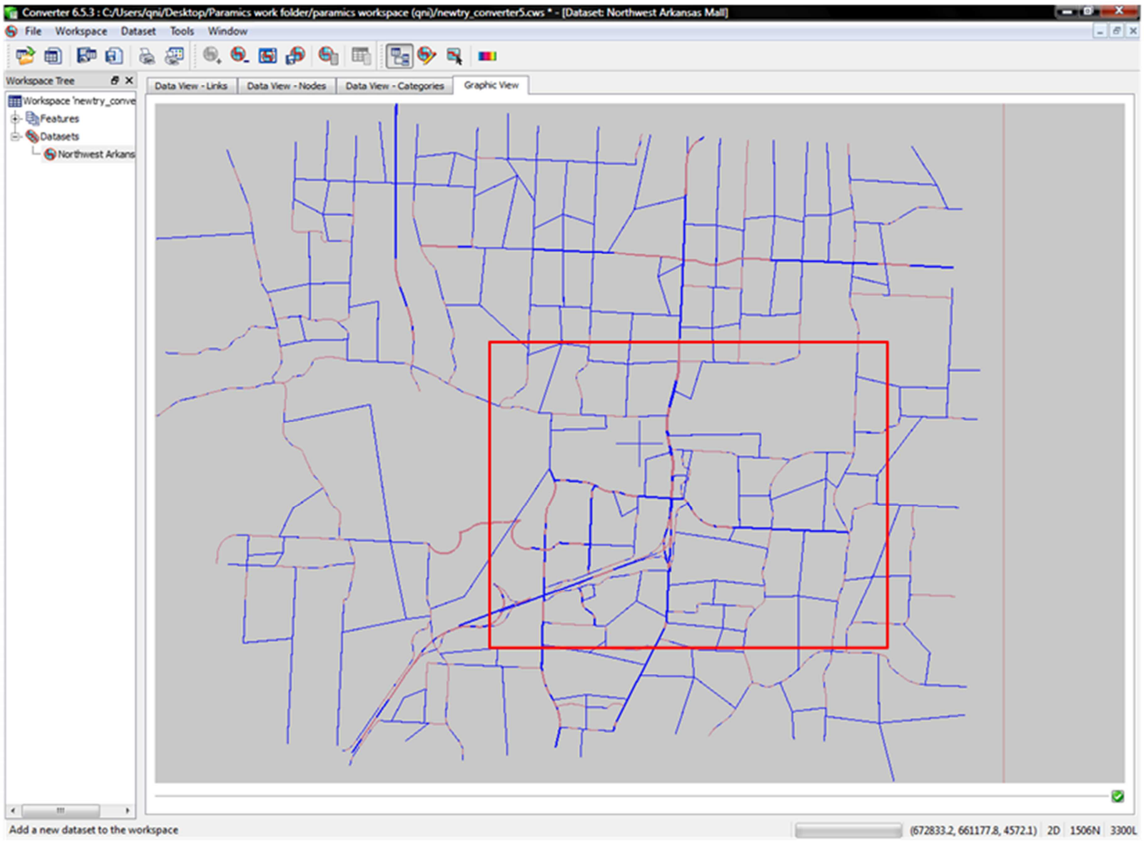


Figure 17. Initial Transformed Traffic Network

The initial transformed simulation network from Converter is shown in **Figure 17**. The area within the red square is the study region. There are numerous errors in the initial network. The adjusted network is presented in **Figure 18**.

Figure 18. Simulated Traffic Network

Trip Generation

The background traffic is used to model the normal traffic on the evacuation roads, and hence the origins of background traffic are not relevant to evacuation simulation model results. In this research, it is assumed that vehicles are simply generated from upstream nodes along a road, and run to the downstream node of the road. Considering the study region and application limitations of Paramics, seven locations were selected to represents origins and destinations as shown in **Figure 19**.

Figure 19. OD Locations for Base Model

Prior to constructing the base model, one additional issue must be resolved. Vehicles observed on stations come from two sources: parking lots and outside the study region. However the base model should represent background traffic conditions as if there is an ongoing evacuation; therefore, it is not necessary to include vehicles from parking lots. The adjusted traffic count data based on reducing travel demand from parking lots is shown in **Table 3**. In the table, RRate represents the reduced rate from the original traffic counts. For example, -20% indicates that background traffic volume is 80% of traffic volumes observed.

Table 3. Modified Traffic Counts at Observation Stations

Locations	16:30-16:45	16:45-17:00	17:00-17:15	17:15-17:30	Subtot	RRate
1	464	490	380	355	1689	0%
2	415	425	340	320	1500	0%
3	298	362	392	328	1380	-20%
4	292	316	340	293	1241	-20%
5	254	255	265	261	1035	-20%
6	164	164	191	200	719	-20%
7	98	98	86	86	368	-40%
8	66	73	82	72	293	-30%
11	142	168	163	181	654	-20%
12	119	128	114	127	488	-30%
13	211	208	222	158	799	-20%
14	309	259	286	266	1120	0%
15	27	27	27	27	108	-50%
16	49	49	49	49	196	0%

Departure Time Model

Based on the observed traffic counts for 15 minute intervals at different locations, the response rate of vehicles for each time period is assumed to be the average proportion of traffic counts for that time period to total traffic counts obtained during study time. For example, the response rate from 16:30 to 16:45 is

$$\frac{\sum(\frac{464}{1689}+\frac{415}{1500}+\frac{298}{1380}+\ \ldots+\frac{119}{488}+\frac{211}{799}+\frac{309}{1120})}{14}=25\%$$

This means that 25% of the vehicles will be released during the time from 16:30 to 16:45. Similarly, the vehicle release rate from 5:30pm to 6:30 was modified and calculated according to **Table 4**.

Table 4. Vehicles Release Rate at different times

Location	16:30-16:45	Percent	16:45-17:00	Percent	17:00-17:15	Percent	17:15-17:30	Percent
1	464	27%	490	29%	380	22%	355	21%
2	415	28%	425	28%	340	23%	320	21%
3	298	22%	362	26%	392	28%	328	24%
4	292	24%	316	25%	340	27%	293	24%
5	254	25%	255	25%	265	26%	261	25%
6	164	23%	164	23%	191	27%	200	28%
7	98	27%	98	27%	86	23%	86	23%
8	66	23%	73	25%	82	28%	72	25%
11	142	22%	168	26%	163	25%	181	28%
12	119	24%	128	26%	114	23%	127	26%
13	211	26%	208	26%	222	28%	158	20%
14	309	28%	259	23%	286	26%	266	24%
15	27	25%	27	25%	27	25%	27	25%
16	49	25%	49	25%	49	25%	49	25%
Average		**25%**		**26%**		**25%**		**24%**

4.3.3. Model Calibration

Calibration Procedures

During the construction of the base model, the method of trial and error was used to calibrate the base model. By viewing simulation animation and comparison between observed data and simulation results, numerous errors can be found and corrected. Key modifications are discussed in more detail as follows.

1) Traffic network coding errors

As discussed in the network coding section, a number of errors exist in the initial traffic network converted from Converter. The correction of networking coding errors is performed throughout the entire simulation model building process. One of the most important corrections is the usage of two ways left turn lanes (TWLTLs) called suicide lanes as illustrated in **Figure 20**. TWLTLs are used for vehicles that change directions or make a left turn toward on-coming traffic; however, this situation is very difficult to model in Paramics. According to the technical notes in Paramics, to some extent

TWLTLs can be modeled by partitioning the lane into a series of turn bays where a road consists of numerous intersections and therefore vehicles can make turn movements at each (virtual) intersection; however this is just an approximation and is not able to simulate conflicting traffic flows. Therefore, TWLTLs are not included throughout our model; however, it is necessary to include left turning lanes at some locations, especially at the intersections illustrated in the red squares in **Figure 20**.

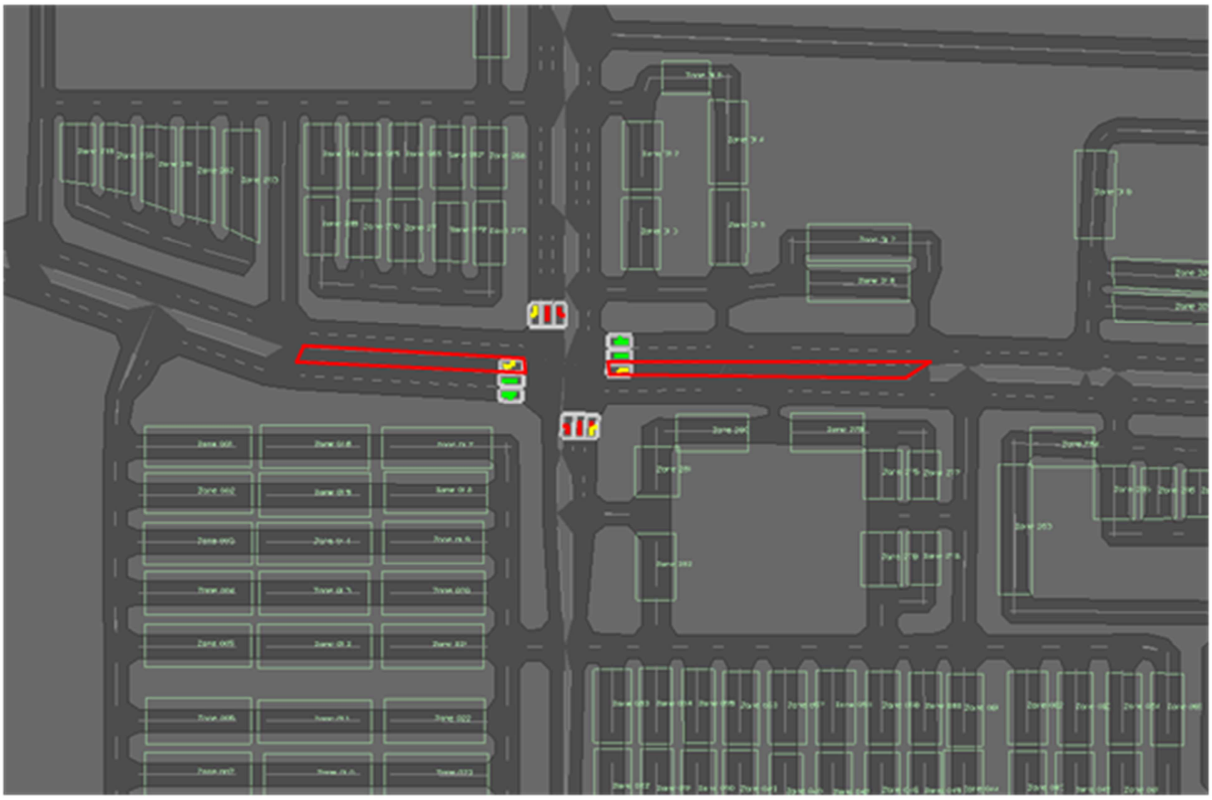


Figure 20. TWLTLs modeling in Paramics

2) OD demand assignment

Since the difference between simulation results and observed traffic counts at observation stations should be small, it is important to distribute demands among these origins and destinations properly. Without technical tools such as Estimator in Paramics to automatically finish demand assignments, it must be done manually. We can initially simply assume that the traffic volumes are the same for the entire road without considering the difference across different road segments as discussed in the assumption section. Then we modify the demand assignment iteratively until the difference between simulation results and observation data is small enough. The method of trial and error was the main approach used.

3) Route assignment

This process is dependent on OD demand assignment. Because background traffic is only on main roads, the route assignment is deterministic with known OD demand assignment. Although this method simplifies the situation, it should be sufficient because the objective of the base model is to model normal background traffic and then simulate the interaction between background traffic and evacuation traffic. The routes used by background traffic are pre-defined rather than random; however, the route assignments of evacuation traffic will be updated periodically through the evacuation process for the reason that evacuees will be desperate to escape from affected region and will change their route if they find a shorter route as time passes within the evacuation scenario. The evacuation model in the research is built on the background traffic model. If we load the background traffic without any operating restrictions in the evacuation model, its route choice will also be dynamically renewed when evacuation traffic route choice is updated. Therefore, the option "Route Control" in Paramics has to be used to control the background traffic.

4) Challenging Problems

Some additional challenging modeling problems included:

- Route control will not function correctly if the number of OD pairs is over some threshold value in a Paramics model. Reducing OD pairs and user defined route assignments can solve this problem.

- Route control may produce vehicle behavior errors causing some vehicles to not follow the route they are supposed to be on. This situation can be improved by deleting defined route choices and making reassignments, or setting some road priorities with higher cost factors, or barring some roads.

Validation Results for the Base Model

Under multiple simulations with different random seeds, the simulated results were obtained. The mean absolute percentage error (MAPE) between observed traffic counts and simulated traffic counts was used as a measure for goodness of fit at different observation stations as shown in **Table 5**.

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|((M_{obs}(t) - M_{sim}(t)) / M_{obs}(t))\right|$$

Table 5. Comparison of Simulated and Observed Traffic Counts

	16:30-16:45			16:45-17:00			17:00-17:15			17:15-17:30			
Loc	Obs	Sim	AD	Obs	Sim	AD	Obs	Sim	AD	Obs	Sim	AD	MAPE
1	464	420.10	9.46%	490	420.60	14.16%	380	418.80	10.21%	355	405.77	14.30%	12.03%
2	415	360.50	13.13%	425	378.50	10.94%	340	363.00	6.76%	320	373.43	16.70%	11.88%
3	298	325.13	9.11%	362	350.833	3.08%	392	345.97	11.74%	328	337.80	2.99%	6.73%
4	292	324.50	11.13%	316	326.70	3.39%	340	317.67	6.57%	293	321.50	9.73%	7.70%
5	254	242.40	4.57%	255	276.50	8.43%	265	271.60	2.49%	261	265.90	1.88%	4.34%
6	164	184.97	12.78%	164	200.33	22.15%	191	192.74	0.91%	200	189.93	5.03%	10.22%
7	98	77.53	20.88%	98	93.80	4.29%	86	92.67	7.75%	86	91.43	6.32%	9.81%
8	66	73.57	11.46%	73	73.567	0.78%	82	72.43	11.67%	72	70.63	1.90%	6.45%
11	142	157.50	10.92%	168	182.57	8.67%	163	181.13	11.12%	181	178.10	1.60%	8.08%
12	119	114.07	4.15%	128	124.40	2.81%	114	120.63	5.82%	127	119.37	6.01%	4.70%
13	211	191.90	9.05%	208	189.27	9.01%	222	214.43	3.41%	158	184.37	16.69%	9.54%
14	309	276.73	10.44%	259	286.83	10.75%	286	281.37	1.62%	266	270.80	1.80%	6.15%
15	27	27.53	1.98%	27	28.267	4.69%	27	27.00	0.00%	27	25.93	3.95%	2.65%
16	49	47.57	2.93%	49	47.467	3.13%	49	48.6333	0.75%	49	47.27	3.54%	2.59%
MAPE	9.43%			7.59%			5.77%			6.60%			7.35%

The comparison of observed and simulated traffic counts within different time intervals can be also presented using column graphs as shown in **Figure 21**, **Figure 22**, **Figure 23**, and **Figure 24**.

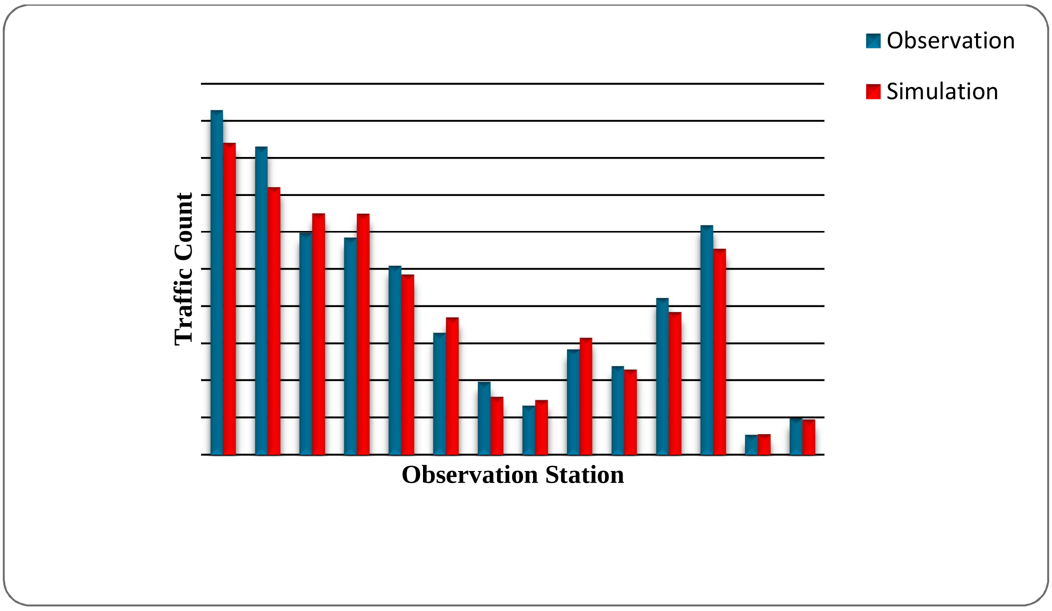


Figure 21. Simulated vs. Observed Traffic Counts from 16:30-16:45 (MAPE 9.43%)

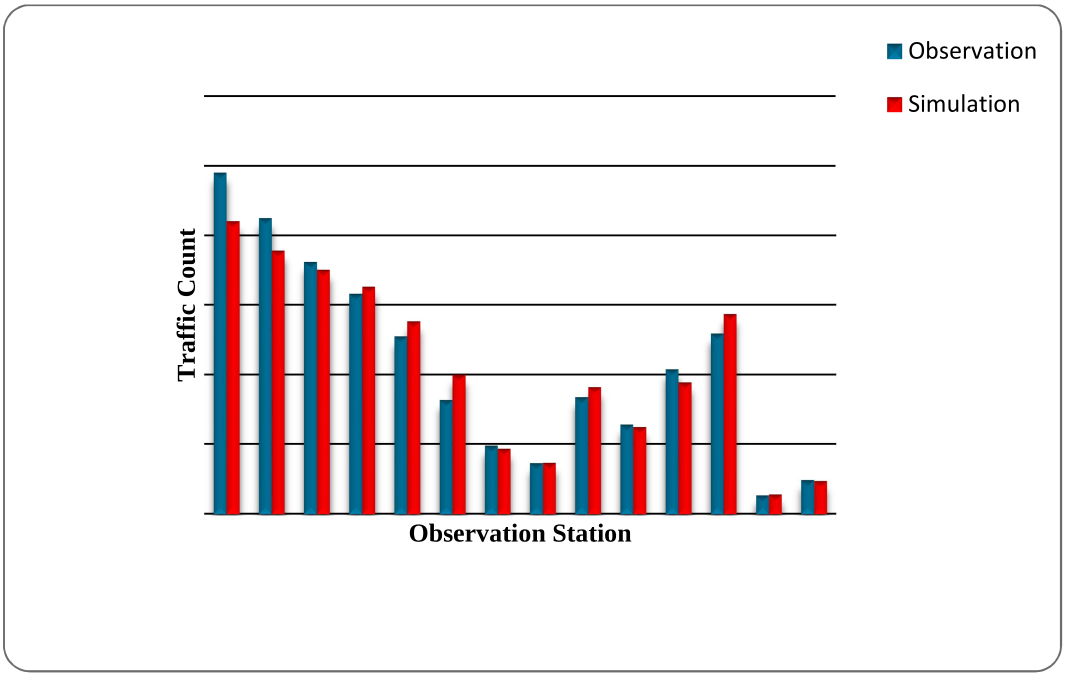


Figure 22. Simulated vs. Observed Traffic Counts from 16:45-17:00 (MAPE 7.59%)

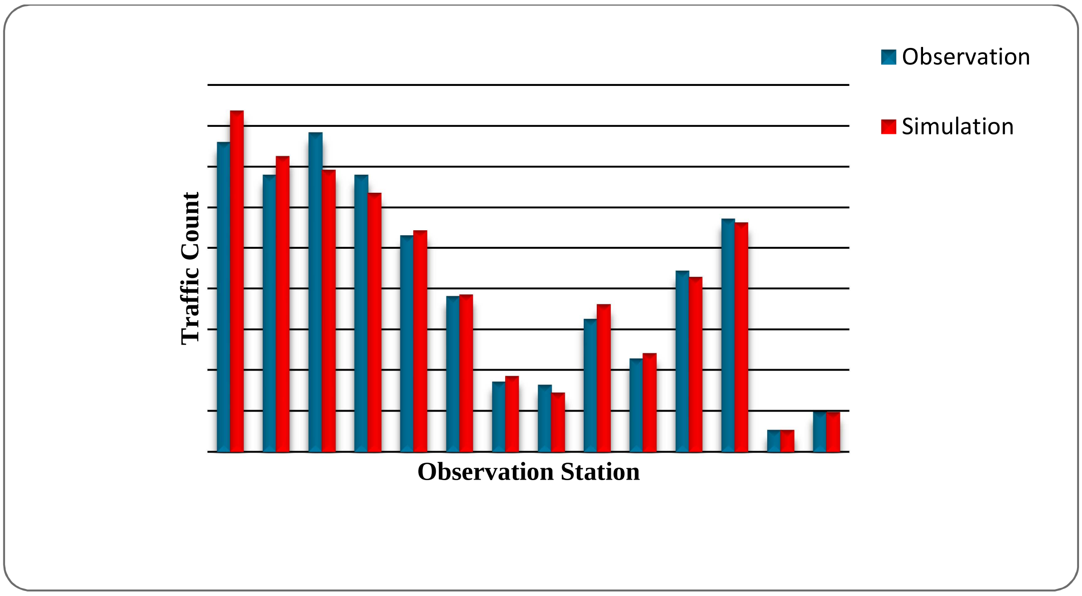


Figure 23. Simulated vs. Observed Traffic Counts from 17:00-17:15 (MAPE 5.77%)

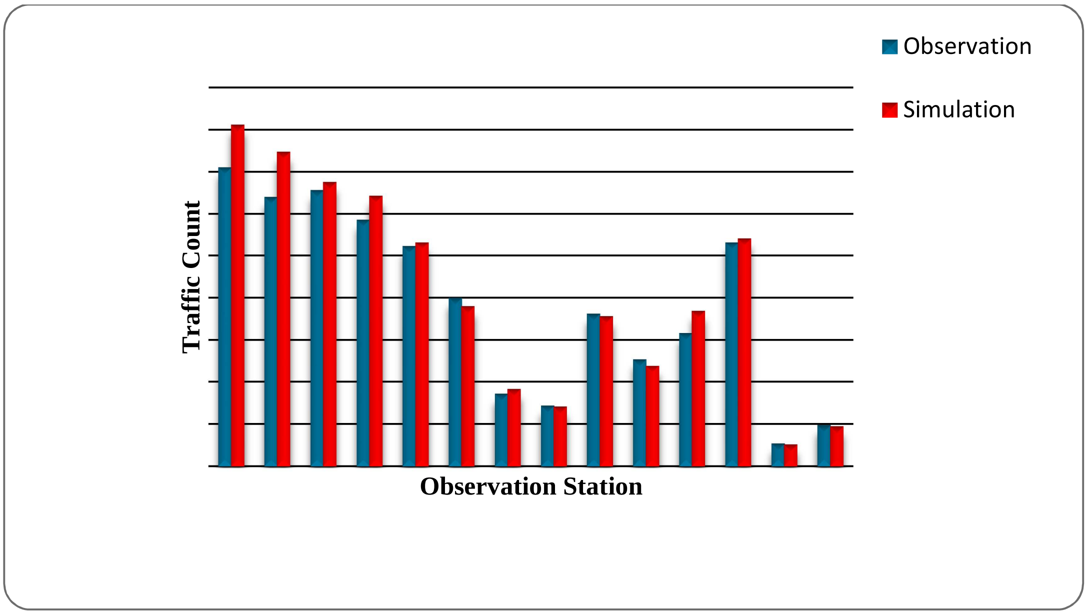


Figure 24. Simulated vs. Observed Traffic Counts from 17:15-17:30 (MAPE 6.60%)

Based on the results, we find that the mean absolute percentage error (MAPE) over all is 7.35% and the maximum MAPE is 9.43%. Thus, we assume that the developed base model is sufficient for modeling the background traffic conditions. And hence, the assumptions made above appear reasonable and can provide a solid base for developing evacuation simulation models.

4.4. Evacuation Model Development

In this section, we primarily focus on the construction of the evacuation model by loading evacuation traffic on the background traffic model built in Section 4.3. Similarly with the construction process of the background traffic model, we first address key modeling issues such as trip generation, departure timing model, and destination choice. We then present a procedure for building the evacuation traffic model in Section 4.4.2. Finally, model calibration is discussed in Section 4.4.3.

4.4.1. Key Modeling Issues

Trip Generation

Prior to modeling the evacuation of resources, the estimation of the number of vehicles from parking zones should be done based on collected data. Suppose one parking row can be divided into several parking zones as illustrated in **Figure 11**. Assume there is a descending priority for drivers to park vehicles from the first row parking zones to the third row parking zones. In other words, drivers first choose to park at the parking zones closer to the entrance to the shopping buildings, then park at the middle parking zones, at lastly they decide to park at the furthest zones. According to the occupancy rate R_{jtd} obtained for parking lot j at time point t of day d, we constructed the simulation models with the occupancy rates of the parking lots at the current occupancy rate and at 85%e, and then simulate the layout of the vehicles in the parking lots.

Figure 25. Vehicle Distribution Curve at Wal-Mart

Take the parking lot of Wal-Mart for instance, most of vehicles are spread over the area around two entrances as illustrated in **Figure 25**, and hence we can draw a distribution curve, given the occupancy rate of the parking lot. Based on the curve and zones in the simulation network shown in **Figure 26**, we can then approximately estimate the average number of vehicles parking in each zone. There are no regular methods to distribute the vehicles to each zone, thus we just distribute them manually.

Figure 26. Parking Zones Layout at Wal-Mart

Given the average number of vehicles in each parking zone, we assume that the number of vehicles x_{ij} originating in a parking zone z_{ij} is Poisson distributed, since the number of vehicles in a parking lot is random at different times of a day.

$$x_{ij} \sim \text{Poisson}(\lambda_i)$$

The λ_i represents the mean number of vehicles distributed manually in each parking zone. This rate may be different for different parking zones. For demand files in Paramics, we can use Java programming to randomly generate the number of vehicles for each origination-destination pair and then generate different demand files for different experimental scenarios. Demand files are discussed when we cover demand generation in Paramics.

Departure Time Model

The concern in the departure timing step is how to load traffic on road networks once the evacuation order is executed. This research assumes that departure time includes both notification time and evacuation preparation time in an evacuation.

There is no doubt that the time for each evacuee to evacuate is uncertain. It is reasonable to make an assumption that the probability density of evacuation departure events varying by time is a Poisson distribution (Cova & Johnson, 2002), because usually evacuation rate is low at the beginning, peaks gradually and later reaches a trough. Based on this assumption, each evacuee can be assigned a time interval during which the departure event happens. Suppose N is a random variable that represents the number of the departure time intervals with T minute increments in the total evacuation time, and assume that N can be described by a Poisson distribution shown in **Figure 27** whose corresponding probability is (essentially) the evacuation rate during a certain time interval:

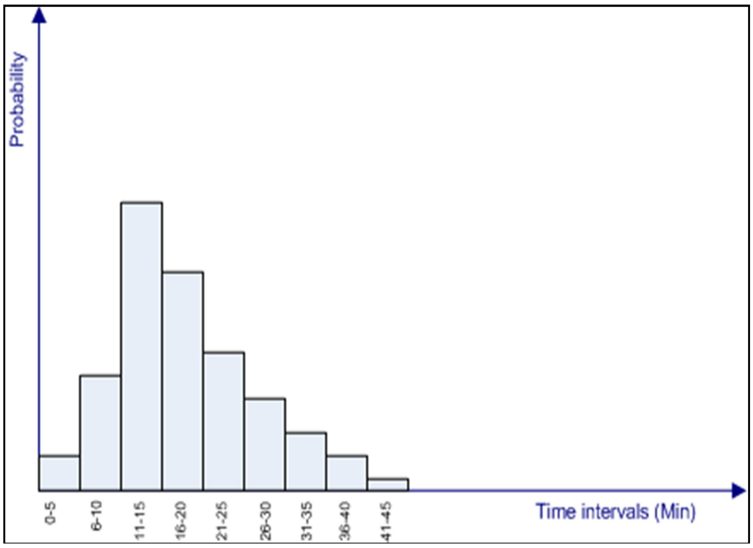


Figure 27. Departure Timing Model with a Poisson Distribution

$$P_n = P\{N = n\} = \frac{\gamma^n e^{-\gamma}}{n!}, \qquad n = 0,1,2\ldots\ldots$$

Where,

γ is the mean number of departure intervals, P_n represents the percentage of vehicles evacuated within the time interval n, and γ*T is the mean departure time for all vehicles.

Based on the equation above, we can determine the temporal distribution of departure vehicles. Let, $X = \sum_{i=1}^{I}\sum_{j=1}^{J} x_{ij}$, be the total number of vehicles generated in zones. Thus $X * P_n$ represents the fraction of vehicles assigned to depart in interval n.

Destination Choice

This step mainly addresses the issue of how to select safe zones in order to assign traffic demand for each OD. The study region can be partitioned into numerous traffic analysis zones (TAZs) based on GIS data in conjunction with population distribution information. Suppose there are limited safe zones with particular populations outside the emergency planning area, each parking zone is deemed to be one demand origin, and people (such as shoppers, pedestrians, or other staff) at each origin come from these safe zones.

Therefore, it is highly possible that people choose to go to a certain safe zones (i.e. their home zone) once the emergency happens. Therefore, the assumption can be made that traffic demands from origins within the planning area to each safe zone are proportional to the population in these safe zones. For a simple base model, the traffic demand from each parking zone can be also divided equally.

4.4.2. Base Model Construction

The evacuation simulation model was initially constructed by loading evacuation traffic flow into the base model. Therefore the background traffic was kept the same in the model. Based on this model, we constrain any modifications of the model to only the model construction assumptions and model parameters, rather than changing the basic simulation network coding. For example, we may change the right of way for roads but not modify the road network such as deleting roads, adding more lanes, reduce two-way road to one-way road, etc.

Basic Assumptions

1) Evacuation occurs suddenly with basic traffic flows.

In this model, the evacuation traffic will be loaded into the affected region after 5 minutes from the beginning of the simulation. This is the simulation "warm up period" when the background traffic has been already loaded in the network, which improves the modeling of the interaction between evacuation traffic and background traffic.

2) Only main roads can be used by vehicles.

This assumption includes two aspects:

- Vehicles traveling on main roads **cannot** drive into parking lots to use routes inside of parking lots.

- Vehicles generated from parking zones can exit directly to main roads, or turn around in parking lots to use the shortest routes they can find; however, if the vehicle exits a parking lot it cannot return to a parking lot.

3) The area outside of the affected region can be regarded as safe zones.
4) Perturbation is 5% and familiarity is 95%. In an evacuation model, route assignments for vehicles are dynamic and updated periodically. With perturbation 5% and familiarity 95%, we assume that not all evacuation vehicles are familiar with routes in the study region and they can choose their routes dynamically at intersections.
5) Traffic flows generated from parking lots are different from the background traffic flows introduced in the background model. (e.g. vehicle mixture by type, evacuation response time, OD demand)

Vehicle mixture by type

Since the project focuses on evacuation from large shopping areas, the vehicles generated from parking lots should be different from normal traffic flows. Due to scarcity of data on vehicle types and different characteristics of vehicles in the aspects of physical attributes and kinematics, this research uses 10 types of cars not including vehicles such as bus, truck, or long vehicles. The proportions among these vehicles are assumed to be the same, that is, 10% for each vehicle type.

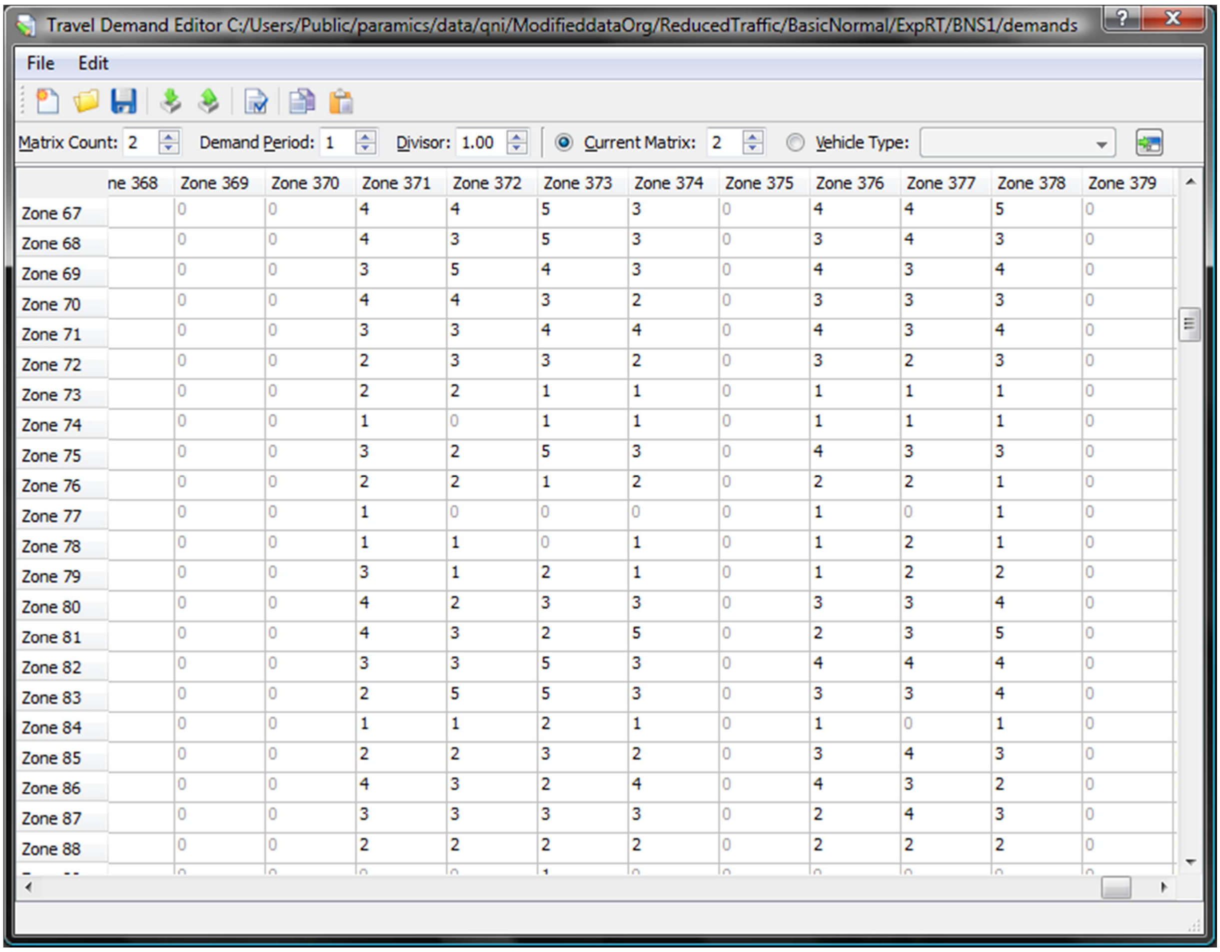
Trip Generation

As discussed previously, there are two types of traffic flows: one is the basic background traffic, the other is evacuation traffic. This project assumes that parking lots are the origins for evacuation traffic and the areas outside of study region are the safe zones or shelters, which serve as the destinations of the evacuees once an evacuation occurs.

Based on the parking lot survey data, we can obtain the average number of vehicles for each zone. Under the assumption that the number of vehicles at different time of the day is a Poisson distribution as discussed in Section 4.4.1, the trips generated from each parking zone can be randomly generated. Since there are almost four hundredzones in our study region, it is impractical to input demand data manually into Paramics. According to the format of demand files in Paramics, we generate the demand files automatically using computer programming. The part of the pseudo code for generating demand files from parking lots is shown in **Exhibit 1**. The format of a demand file in Paramics which is generated from programming is illustrated in **Figure 28**.

Exhibit 1. Pseudo-code for Trip Generation in Parking lots

```
READ  a value from average data file as Avg
      SET   inputdata equal to the Avg
      SET  row equal to 1
      WHILE  (row<=OD and inputdata !=null)
         SPLIT inputdata and store into an array
         SET  avg=array[1]
             IF  Avg>0
           PRINT  “from” + "     " +row+"     "
           FOR each value X&Y from OD
              IF  (X!=Y, 371<=Y<=378 and Y!=375) THEN
                 CALL rgn.getValue() from Poisson class
                 SET  z=rgn.getValue()/(7*divisor)
              ELSE
                 SET  x=0
              ENDIF
              IF  Y<384
                 PRINT z and "    "
                   ELSE
                 PRINT z and "  "
              ENDIF
           ENDFOR
          ELSE
            PRINT “from” + "     " +row+"     "
            FOR  each value Y of OD
             z=0
             IF  Y<384
                 PRINT z and "    "
                 ELSE
                 PRINT z and "  "
             ENDIF
            ENDFOR
         READ  a line from average data file
             SET   inputdata equal to the Avg
   ENDWHILE
   ClOSE output file and  input file
```



	ne 368	Zone 369	Zone 370	Zone 371	Zone 372	Zone 373	Zone 374	Zone 375	Zone 376	Zone 377	Zone 378	Zone 379
Zone 67		0	0	4	4	5	3	0	4	4	5	0
Zone 68		0	0	4	3	5	3	0	3	4	3	0
Zone 69		0	0	3	5	4	3	0	4	3	4	0
Zone 70		0	0	4	4	3	2	0	3	3	3	0
Zone 71		0	0	3	3	4	4	0	4	3	4	0
Zone 72		0	0	2	3	3	2	0	3	2	3	0
Zone 73		0	0	2	2	1	1	0	1	1	1	0
Zone 74		0	0	1	0	1	1	0	1	1	1	0
Zone 75		0	0	3	2	5	3	0	4	3	3	0
Zone 76		0	0	2	2	1	2	0	2	2	1	0
Zone 77		0	0	1	0	0	0	0	1	0	1	0
Zone 78		0	0	1	1	0	1	0	1	2	1	0
Zone 79		0	0	3	1	2	1	0	1	2	2	0
Zone 80		0	0	4	2	3	3	0	3	3	4	0
Zone 81		0	0	4	3	2	5	0	2	3	5	0
Zone 82		0	0	3	3	5	3	0	4	4	4	0
Zone 83		0	0	2	5	5	3	0	3	3	4	0
Zone 84		0	0	1	1	2	1	0	1	0	1	0
Zone 85		0	0	2	2	3	2	0	3	4	3	0
Zone 86		0	0	4	3	2	4	0	4	3	2	0
Zone 87		0	0	3	3	3	3	0	2	4	3	0
Zone 88		0	0	2	2	2	2	0	2	2	2	0

Figure 28. Format of Demand Files generated from Programming

Destination Choice

For the study region, seven safe zones distributed around the outside of the emergency region are designed to release background traffic and absorb evacuation traffic as shown in **Figure 29**. In this model, we assume that the probability that a vehicle from a parking lot chooses any one of the safe zones to go is the same, that is, vehicles generated from a parking zone will be equally distributed to seven safe zones.

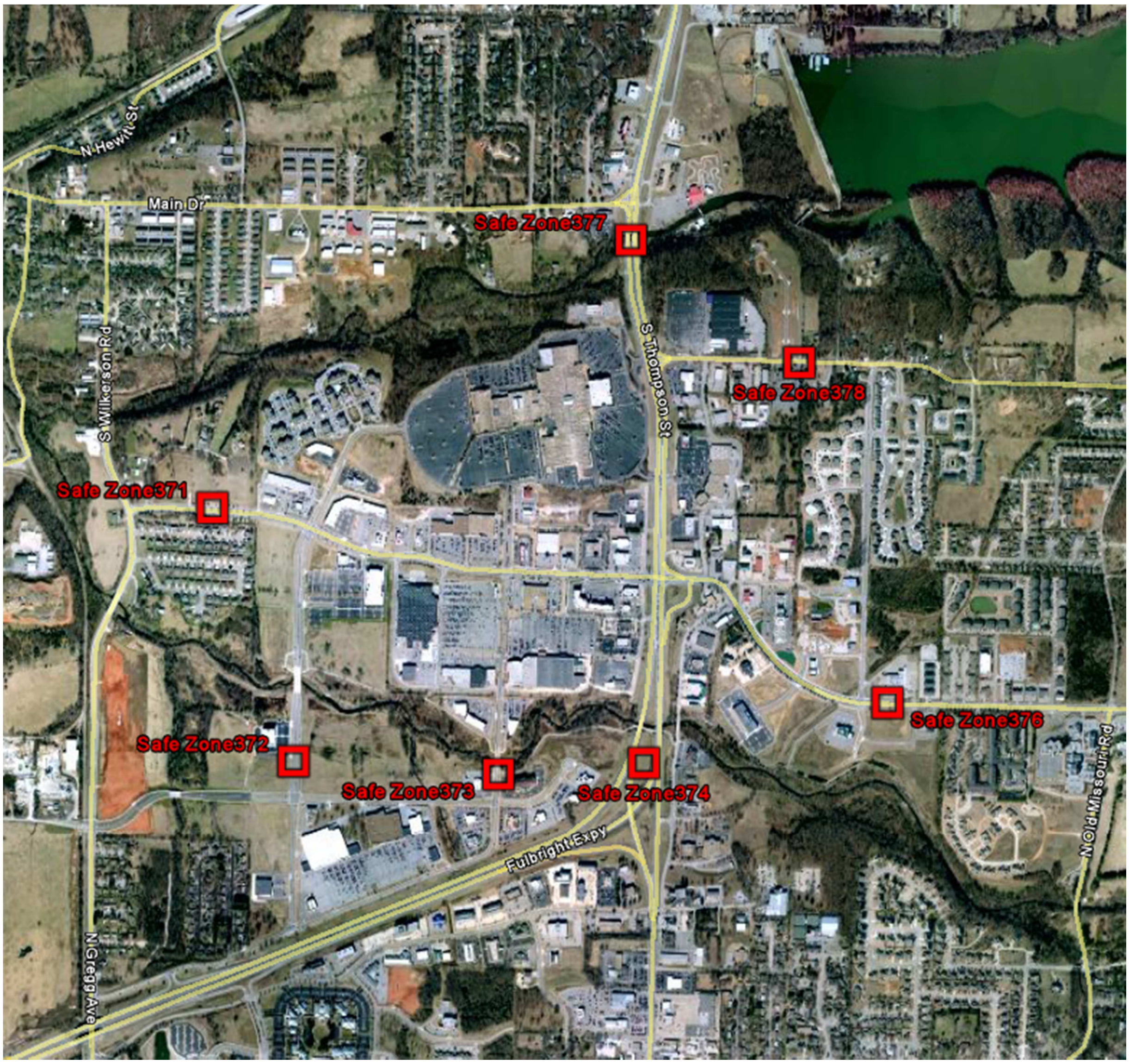


Figure 29. Selected Locations of Safe Zones

Departure Timing Model

Response time is the time from when evacuees have realized the emergency and start to evacuate. Its value is variable for different evacuees. Suppose that the response time for evacuees in the affected region is a Poisson distribution with mean time 15 minutes, which is the time of receiving an evacuation order, exiting a shopping building, walking to their vehicles, and beginning to drive out of parking lots. The departure timing model takes the response time and translates it into traffic release rates for different time periods at the start of an evacuation. The calculated traffic release rates onto the network are shown in **Figure 30**.

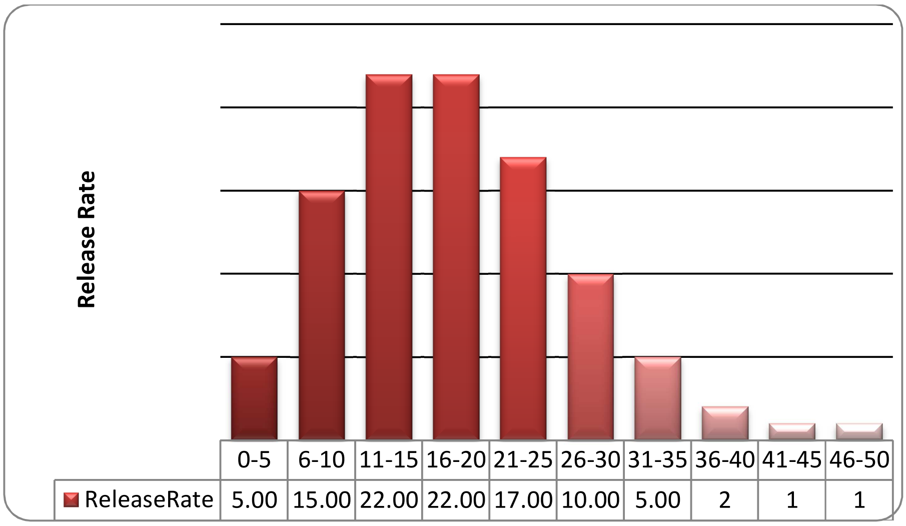


Figure 30. Response Rate for Evacuation Traffic

4.4.3. Evacuation Model Calibration

When observing the animation of initial evacuation simulation model, we can find numerous unrealistic situations, which must be corrected:

1) Traffic congestion in parking lots

During simulation model runs, many vehicles became deadlocked within the regions circled with red lines in **Figure 31**. The vehicles wait for an excessive amount of time to get out of the region. For instance, most of the vehicles at intersection A can select road 1 rather than road 2. This increases the likelihood that vehicles will be stuck on road 1. However, there is space available on road 2. The vehicles on road 1 are supposed to select road 2 if there is space available on road 2. In this situation, we can iteratively modify the road priority where these deadlocks occur.

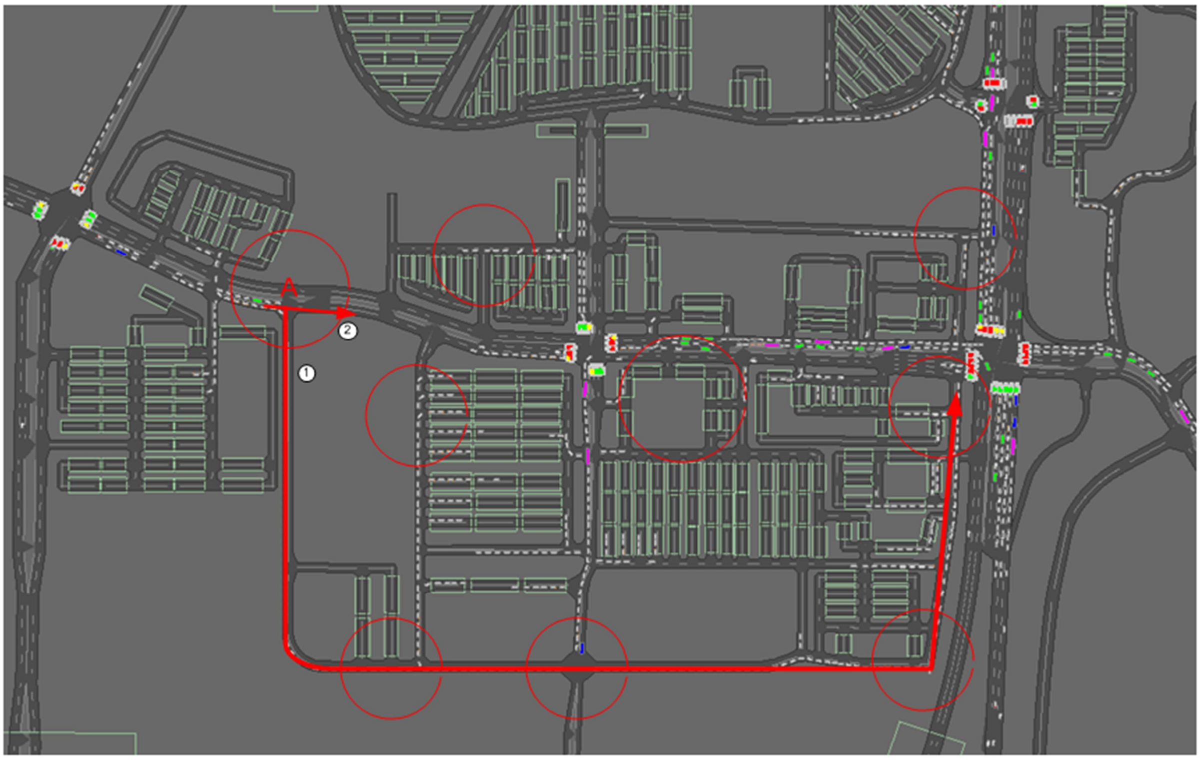


Figure 31. Traffic Congestion in Parking Lots

2) Intersection Congestion

Vehicles become deadlocked at some intersections and cannot move at all, which cause terrible traffic gridlock during the evacuation; hence evacuation times tend toward infinity. In **Figure 32**, for instance, there are multiple conflicting (crossing) traffic flows. Thus, vehicles can become entangled within the intersections. There are two methods available to avoid deadlock congestion at the intersections and parking lots: Lane priority changes or using the blockage removal tool in Paramics. The former aims to constrain the freedom of vehicles choosing routes. For instance, we can bar vehicles not to enter parking lots and prevent them from turning around in the parking lot after they are generated. The latter can reduce the congestion by removing the deadlocked vehicles; however this is not appropriate for evacuation. Because one of the project objectives is to identify traffic bottlenecks, we need to identify where traffic congestion occurs.

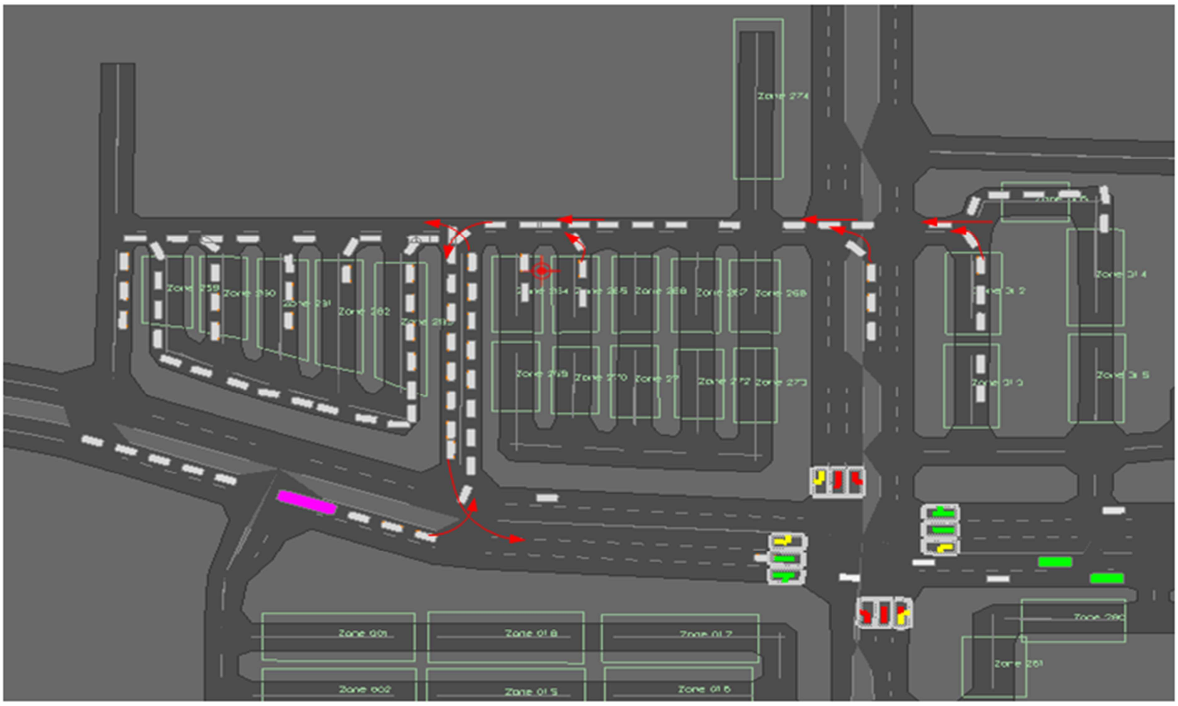


Figure 32. Traffic Congestion at Intersections

3) Left turn gridlock and lane choice

When calibrating the simulation network, the turning movements in the intersections do not always operating in a realistic manner. For example, there are 3 lanes: lane 1, land 2, and lane 3, in road #1 as shown in **Figure 33.** Lane 3 is for left turns from intersection A to intersection D. In this research, the traffic is constricted to run on Road #1, and not allowed to make turning movements at intersection A, B, and C. Therefore, vehicles that will turn left on intersection D are supposed to change to lane 3 as soon as possible if they find there are many vehicles waiting ahead in lane 3. However, as shown in the figure, most of the vehicles do not tend to move to lane 3 until they arrive at intersection C, and at that time there are many vehicles queuing in the lane 3 from intersection D to intersection C. In this situation, these vehicles have to wait at lane 1 or lane 2 until there is a gap for them to move to lane 3. Thus, these waiting vehicles will prevent vehicles moving towards other destinations (e.g. vehicles moving directly to the West) from moving forward, and hence cause traffic gridlock. In reality, this is extremely unlikely, vehicles turning left will only queue or wait on lane 3 not lane 1 or lane 2, and they may begin to change to lane 3 from intersection A.

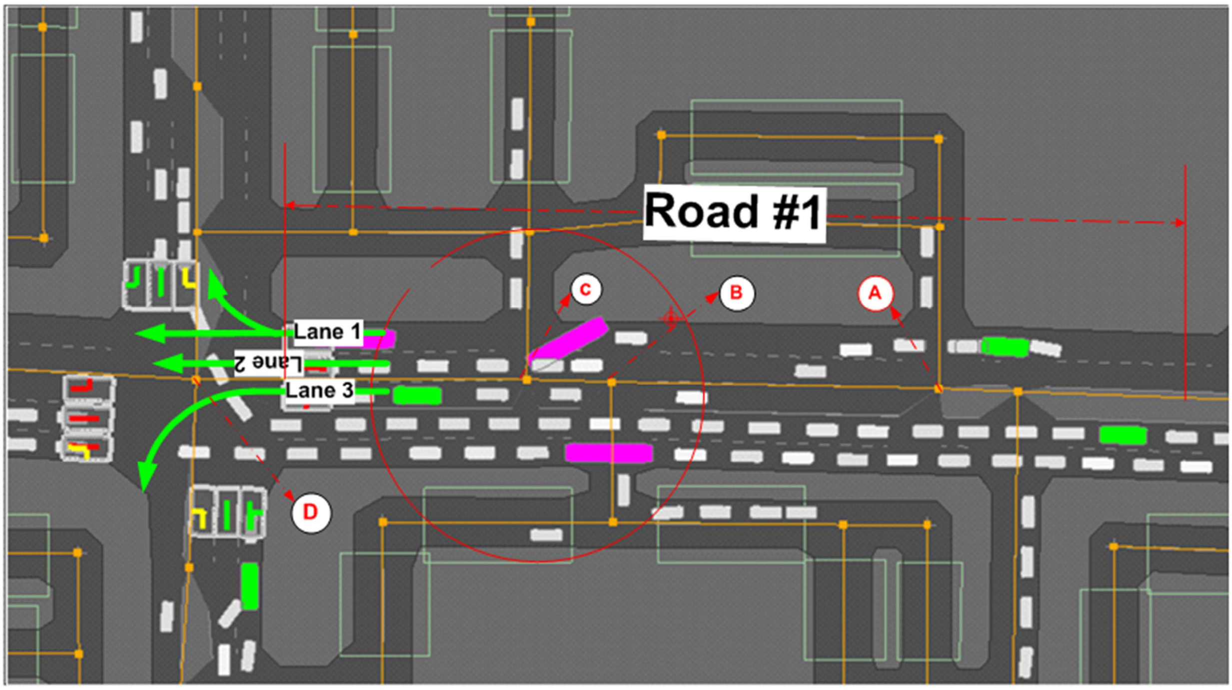


Figure 33. Left Turn Gridlock and Lance Choice

In Paramics, there are two methods that can be applied to solve this problem. One is changing the signpost distance or signrange distance as shown in pink line in **Figure 34**.

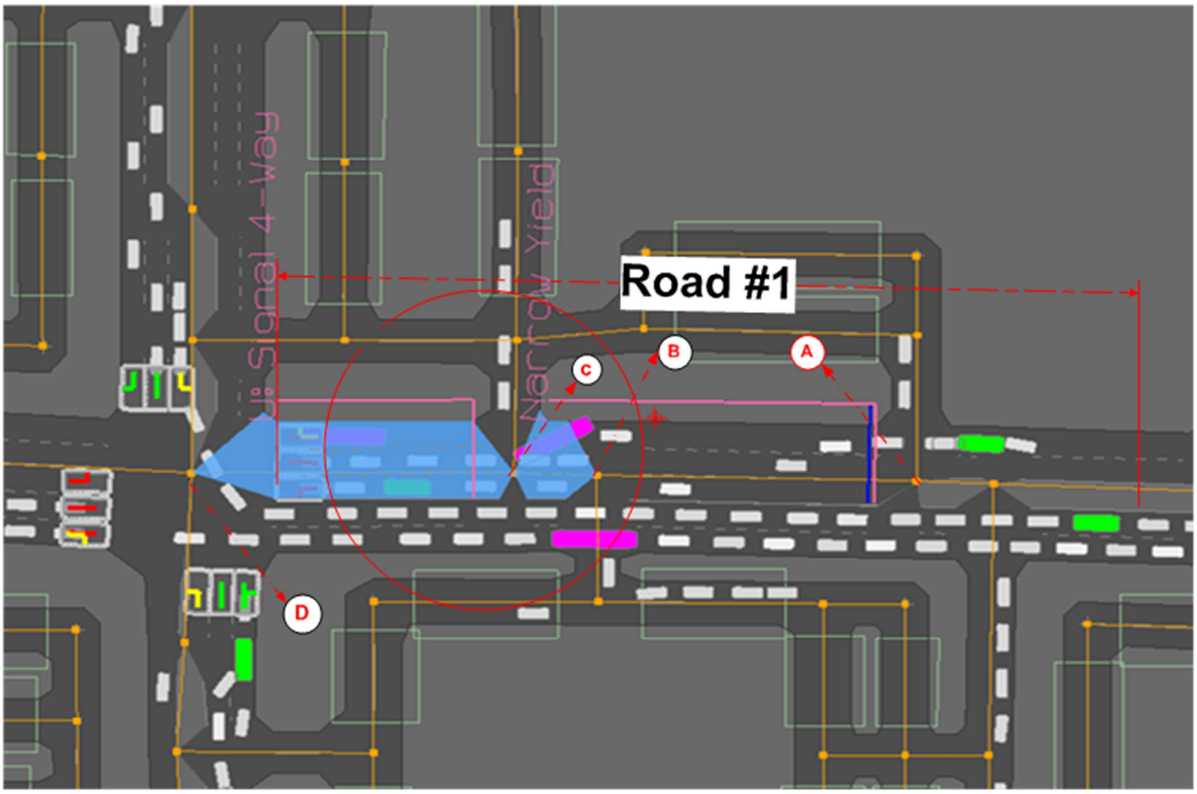


Figure 34. Sign-post Distance and Sign range

Sign posting distance is the distance from hazards where drivers will realize the hazards ahead. Hazards are generally intersections, forks, diverge, etc. Once a driver sees the hazard such as an intersection he will decide based on this pre-defined distance if a lane change such as making a left turn movement is required. If a lane change is necessary, the vehicle will attempt to change into the required lane by the normal lane changing procedure. In Paramics, vehicles have to wait for accepted gaps on the lane they attempt to change in case of a collision, where a gap is the distance between a leader vehicle and a following vehicle. Therefore if a gap is not available immediately the vehicle will carry on until a gap is available. Based on this information, we should theoretically extend the signpost distance as long as possible, at least extending to intersection A; however, this does not work and we cannot change the signpost to A.

The other method is "Lance Choice" in Paramics. Lane Choice is more like a pre-defined route choice, where we can define certain routes and force vehicles to follow them. For example, we can force all vehicles to choose the left turning lane from node A as shown in **Figure 35**.

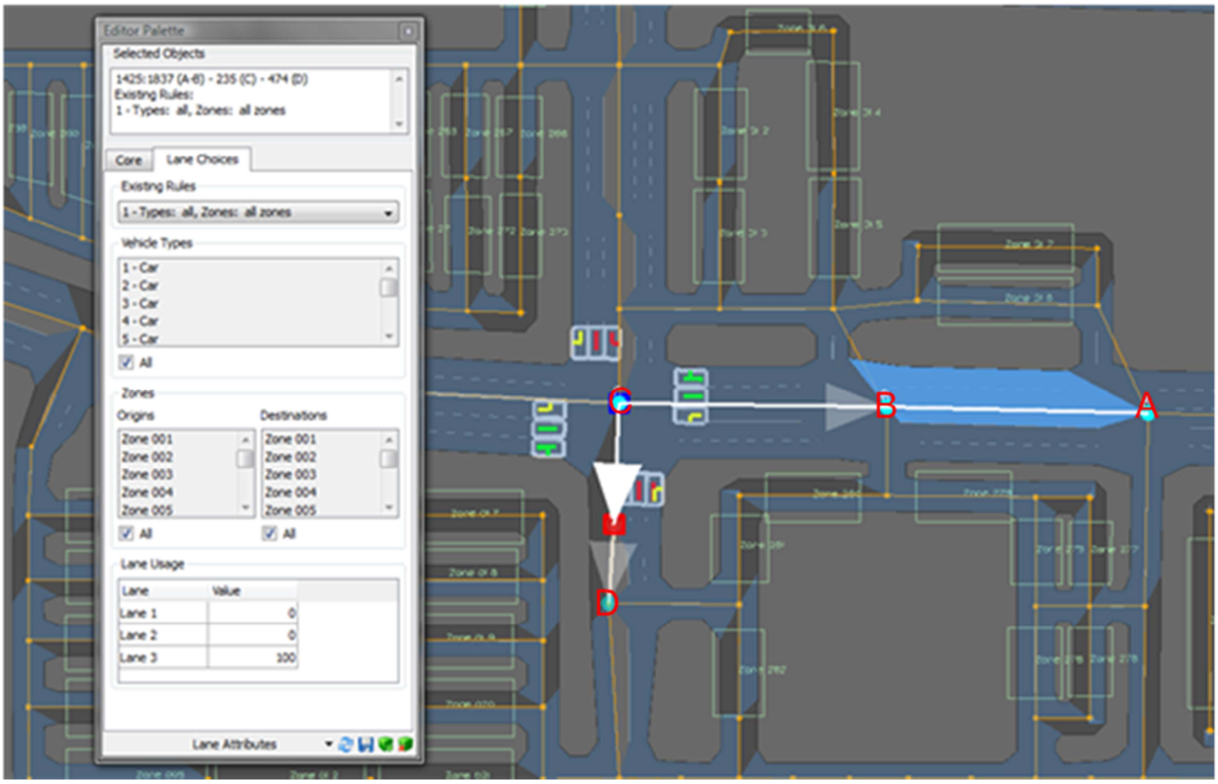


Figure 35. Lane Choice Rule in Paramics

Theoretically, this should reduce the congestion in the intersection, because all the vehicles will tend to move to lane 3 first and vehicles turning left will not encounter conflicting flows. However, the simulation results indicate that the method does not improve the congestion.

Based on these calibration procedures, the model cannot represent the reality appropriately; therefore we have to calibrate the model by modifying the basic road network described as follows.

1) Modify network coding by changing some roads to one way

Because the evacuation traffic is not allowed to enter parking lots after they depart, the inward link can be barred or simply modeled with one way traffic. In the model, road B, road C, and road D was change to be one way, and then the signpost distance increased from 172.5 in to 307.9 ft as shown in **Figure 36**. The system performance was improved, and the corresponding total evacuation time for evacuation traffic was decreased.

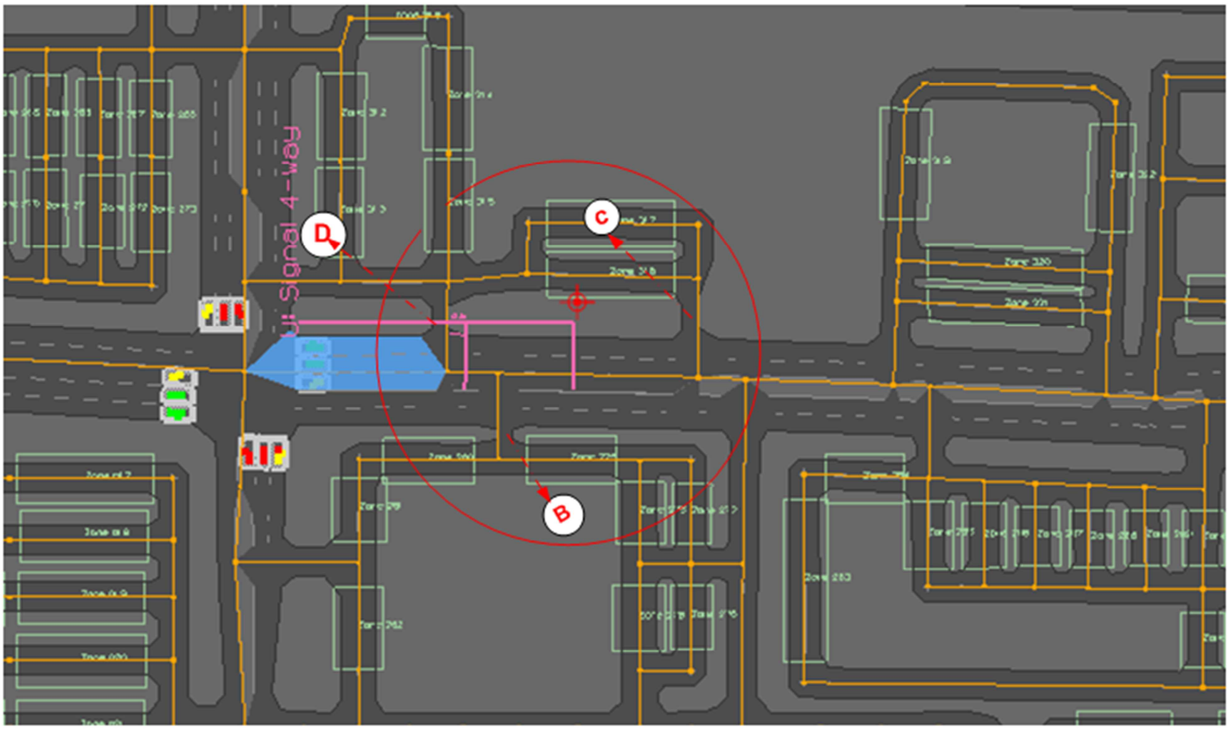


Figure 36. Modified model with one way

2) Change the priority of traffic flows

The priority of traffic flows generally means that we can set the right of way for different roads on the intersections. In addition, we can also take advantage of the Force Cross function in Paramics to generally control the waiting time for vehicles crossing intersections. Since this is an evacuation model, it is unrealistic if vehicles wait too much time at intersections. In the initial model, however, it was observed that many vehicles wait too much time at the intersections for a gap to merge into their desired traffic stream.

By using the **force merge** and **force cross** tools in Paramics at the exits of parking lots, we can force vehicles to cross intersections after they wait a certain time. The red points in the **Figure 37** are the roads where the Force Across function was applied within the model. However, one of the deficiencies of this approach is that the patience parameters in Paramics to control the waiting time cannot be modified. Based on the technical notes of Paramics, the default patience time is about 0.5 - 2 minutes.

Figure 37. Roads with Force Cross function

3) Change the feedback period

In Paramics, vehicles update their routes according to route cost per cycle. Generally, the route cost is the time that the vehicles take to get through the road, and the time may be different at different times. For example, if there is serious congestion on the road, the cost becomes too high to be selected by drivers. In Paramics, the feedback period is the time at which road times are fed back into road cost calculations. At the beginning of each feedback period, Paramics performs route cost calculations in order for vehicles to choose the route they desire. The length of feedback period affects directly the route choice of vehicles. For example, if the feedback period is 5 minutes, then vehicles will update their route choice every 5 minutes, and it also means that they will keep on the chosen route for at least 5 minutes even though the route has serious traffic gridlock. Theoretically, the smaller that the feedback period is, the more vehicles are able to update their routes. However, the smaller feedback periods also require higher CPU time and it is highly possible that vehicles keep finding the shortest roads all the time, which can also cause serious congestion. Therefore, we have to try different feedback periods for specific simulation models. In the project, we will use the feedback period of 3 minutes based on observed preliminary simulation results. Multiple simulation runs have to be calibrated individually, and then all the adjustments must be applied to one model before being able to run in batch mode.

Based on these strategies, the modeling of the base evacuation simulation model was completed. In the next section, different experiments are performed for different evacuation scenarios based on the base evacuation model.

4.5. Experimental Scenarios, Results, and Analysis

Evacuation may be dependent on various factors such as traffic control policies, evacuation routes situation and selection, evacuation beginning time, etc. This section tests the effectiveness of the evacuation models by developing different scenarios, based on the constructed evacuation model in the Section 4.3. We will start with descriptions of the evacuation scenarios and provide corresponding assumptions. We then post process each evacuation scenario and perform analysis of results in Section 4.5.2. Finally, an overall analysis is provided in Section 4.5.3.

4.5.1. Evacuation Scenario Development and Assumptions

The project is based on the assumption that a certain emergency (e.g. fire, terrorist attack, chemical pollution) occurs somewhere within the study area. This document only focuses on the process of how vehicles evacuate to arrive at safe areas as long as the emergency takes place, and how they affect the surrounding traffic flows.

According to data availability from CAST, the simulation models were constructed based on the forecasted traffic condition of 2010. Based on the characteristics of the study region, there are several factors that may affect the evacuation.

1) Occupancy Rate

The origins of vehicles are parking lots in the shopping areas, and hence the occupancy rate of each parking lot will influence the total evacuation time. In this project, we consider only two occupancy rates: current occupancy rate without emergencies and an 85% occupancy rate.

2) Background Traffic

During evacuation, the government may guide the operation of background traffic. For example, police may stop outside traffic flow from entering the affected region. In this project, we consider three situations concerning the background traffic as follows:

- The background traffic stopped suddenly after 15 minutes from the beginning of the evacuation.
- The background traffic is reduced gradually after 15 minutes from the beginning of evacuation, according to a Poisson distribution.
- The background traffic remains the same as the traffic flow from 4:30 pm to 5:30 pm.

3) Traffic operations/ network configuration

In the project, we assume that traffic signals operate normally without considering interventions from the traffic department.

4) Study area population

Since emergencies may occur at any time, both peak hours and off-peak hours are important; however, only peak hours will be covered in the project in order to examine the effectiveness of evacuation strategies in the context of worse case scenarios.

5) OD matrix and route assignment

Based on the discussion in the Section 4.4, parking lots are demand origination points in the study area, and the safe zones are the areas outside of the study region. Evacuees (i.e. vehicles) are able to select any direction for escape. Since driver behavior during an evacuation may be different when compared with the normal conditions, it is very difficult, if not impossible, for us to accurately predict the traffic demand on each route. As an alternative, we assume a balanced route assignment approach, where the proportion of the vehicles originating from a certain zone towards each safe zone is the same. In addition, evacuation traffic is loaded into the simulation network after 5 minutes from the beginning of the evacuation to better model the interaction between background traffic and evacuation traffic. Based on preliminary results, the background traffic is completely distributed around the study region after 5 minutes.

6) Response rate

A Poisson distribution model discussed in Section 4.4.1 is used to model the response rate.

We only vary two variables: response rate and background traffic operation level, with which six evacuation scenarios can be developed as illustrated in **Figure 38**. Each scenario is described in more detail as follows.

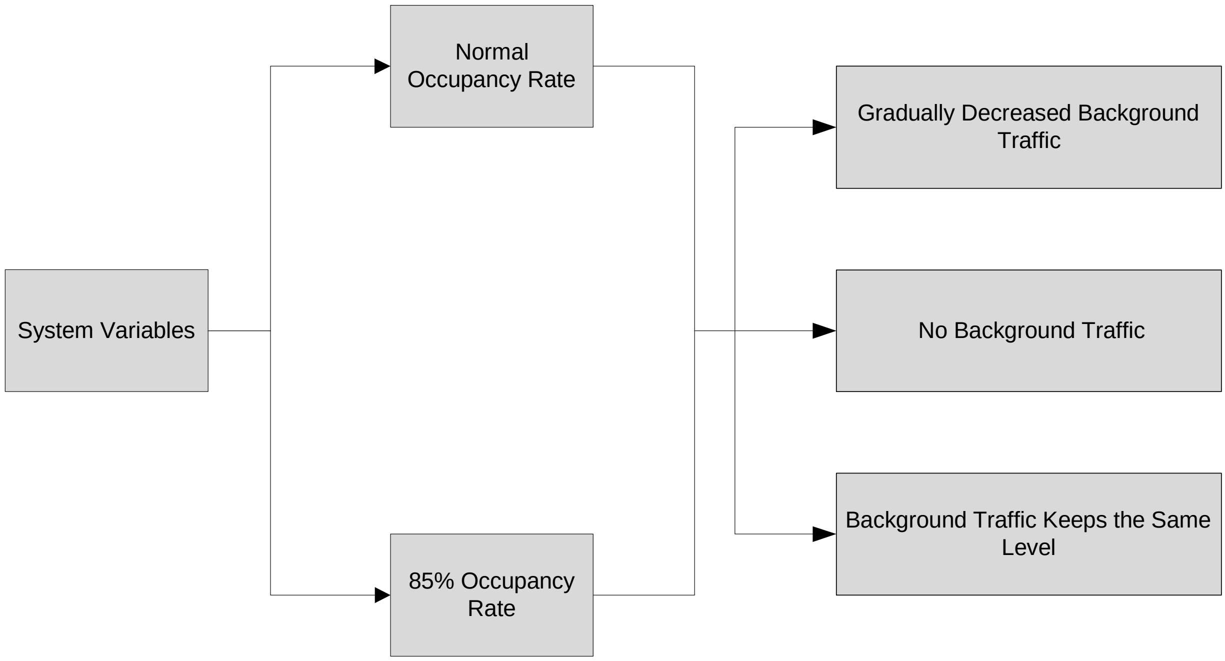


Figure 38. Evacuation Scenarios Development

- **Evacuation Scenario 1** - Normal occupancy rate without evacuation and the same background traffic level during evacuation.

This scenario is the combination of the following factors:

- The background traffic will be the same during evacuation, assuming no intervention from police or government.
- The occupancy rates of parking lots are the same as normal conditions.
- The response time model for the evacuees is based on a Poisson distribution.
- The number of vehicles generated from parking lots, that is, the number of evacuees, is also Poisson distributed.

- Other factors remain the same as with the base evacuation model constructed in Section 4.3

Prior to doing experiments, we should modify demand files of background traffic. In this scenario, we assume that the background traffic remains at the same level during evacuation, which is from pm 4:30 to pm 8:30. The procedure of constructing the demand files for background traffic is as follows:

- In the background traffic model, the simulation time is only one hour from 16:30 to 17:30; however, the total evacuation time in this scenario is estimated to be over 3 hours, based on pilot experiments For constructing the evacuation model, we therefore not only need to add evacuation traffic into the background traffic model, but also we need to extend the total simulation time. For this research, we decided to use 4 hours of the total simulation time, which consists of two periods: period 1 from 16:30 to 17:30 and period 2 from 17:30 to 20:30. The demand file for period 1 was kept the same as the demand file of the background traffic. .
- Increase the demand of background traffic for demand period 2 as three times of the demand of demand period 1. Then model calibration should be made in order to keep the demand release rates the same for the two demand periods.

The modified release rate for evacuation traffic is shown in **Figure 39**. We can find the average difference between two periods in terms of release rates are about 1.28%, which indicates that our modification is acceptable.

Org Zone	Des Zone	Period 1 demand	Reduced Demand (-10%)	Period 2 Demand	Period 1 RRate/15 mins	Period 2 RRate/15 mins	MAPE
371	376	488	439	1317	117.12	118.53	1.20%
371	372	108	97	291	25.92	26.19	1.04%
372	371	196	176	528	47.04	47.52	1.02%
373	374	260	234	702	62.4	63.18	1.25%
373	376	33	30	90	7.92	8.1	2.27%
375	371	291	262	786	69.84	70.74	1.29%
375	384	1380	1242	3726	331.2	335.34	1.25%
376	371	376	338	1014	90.24	91.26	1.13%
376	373	368	331	993	88.32	89.37	1.19%
377	383	1120	1008	3024	268.8	272.16	1.25%
383	374	1241	1117	3351	297.84	301.59	1.26%
384	377	799	719	2157	191.76	194.13	1.24%
383	371	50	45	135	12	12.15	1.25%
						AvgMAPE	1.28%

Figure 39. Modified Release Rate for Demand Periods

- **Evacuation Scenario 2 -** 85% occupancy rate and the same level of background traffic

This scenario is similar with evacuation scenario 1, except that the occupancy rate is changed from the current occupancy rate to an 85% occupancy rate. This scenario is to investigate the effects of occupancy increments on the entire evacuation. This is the worst case where both occupancy rate and background traffic level are the highest in the project.

- **Evacuation Scenario 3 -** Normal occupancy rate without evacuation and background traffic will be stopped suddenly.

In this situation, we assume that evacuation will be manipulated by the police or department after a certain time from evacuation beginning (e.g. 15 minutes in the project). The background traffic operates normally from the beginning of the evacuation, and is shut down immediately when police arrive and stop all vehicles from entering into the affected region.

Assumptions:

- The time before police control of the background traffic is 15 minutes.
- The traffic lights are fixed cycling time not a sensor light.
- The background traffic is the same during the 15 minutes from the beginning of the evacuation.
- Other factors remain the same as with base evacuation model constructed in Section 4.3

➢ **Evacuation Scenario 4 -** 85% occupancy rate evacuation and background traffic will be stopped suddenly.

This scenario is similar with evacuation scenario 2, except that background traffic will be turned off after 15 minutes.

➢ **Evacuation Scenario 5** - Normal occupancy rate with evacuation and gradually decreasing background traffic.

In this scenario, we consider the situation that police will guide the operation of traffic flow entering into the study region and reduce the inward traffic gradually to zero, instead of stopping traffic flow completely. In this project, a Possion distribution is employed to simulate the reduced release rate of background traffic. The corresponding assumptions include:

- The time before reducing background traffic is 15 minutes from the start of the simulation.
- Background traffic is the same as the base model during the first 15 minutes.

- Other factors remain the same as the base evacuation model constructed in Section 4.3

The release rate of background traffic in the project is illustrated in **Figure 40**.

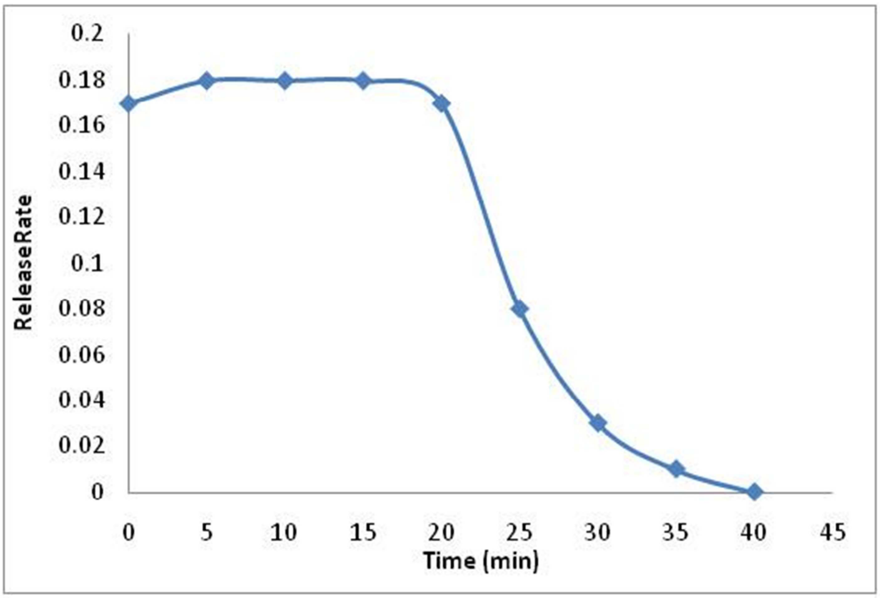


Figure 40. Reduced Release Rate of Background Traffic

- ➢ **Evacuation Scenario 6 -** 85% occupancy rate and gradually decreasing background traffic.

This scenario is the same as scenario 5, except that occupancy rate is changed from normal occupancy rate to an 85% occupancy rate.

4.5.2. Scenario Results and Analysis

Considering the nature of randomness of simulation results, multiple simulation replications are required, where models are the same for each evacuation scenario except for the demand files. The overview of the procedures for building multiple simulation replications and post-processing simulation results are presented in what follows.

1) Generate demand file randomly

According to the pseudo-code described in Section 4.3 for evacuation trip generation, we generate randomly 30 demand files by using Java programming. In each demand file, the number of vehicles escaping from each parking zone is stochastic.

2) Build multiple simulation replications

With demand files generated above, 30 simulation replications are constructed for each evacuation scenario.

3) Calibrate simulation models

When we build multiple simulation replications with different demand files based on the original model of each evacuation scenario, it is highly possible that some replications will not run appropriately with the generated demand file. For example, the model can run with some demand files, it may however, fail to run well with other demand files. In this case, we have to modify the original model to make it run for all demand files.

4) Analyze simulation results

This step focuses on post-processing simulation results. In the project, we extract the desired data from the log files of multiple simulation replication models which are run in batch using Processor in Paramics. For example, we can automatically obtain travel time data of vehicles from each log file of the simulation replications and store them into one file by Java programming, and then analyze the data using statistics analysis packages such as JMP.

In this step of the simulation analysis, the key measures of performances include:

- Total evacuation time

The study region has more than 7 parking lots. The total evacuation time analysis without considering particular parking lots or parking zone can provide us with information such as mean overall evacuation time, maximum evacuation time, and cumulative density function of the number of vehicles evacuated. Based on this, we can estimate the risk of evacuation faced by shoppers in the commercial shopping area, if the time to evacuate is given and limited.

- Evacuation time analysis for different parking lot

There are multiple parking lots within the affected region as shown in **Figure 41**. The evacuation time may vary by parking lot, which is crucial for local emergency planners. In the project, we present evacuation time for several key parking lots. The evacuation time distribution for special parking lots is tabulated in Appendix B1.

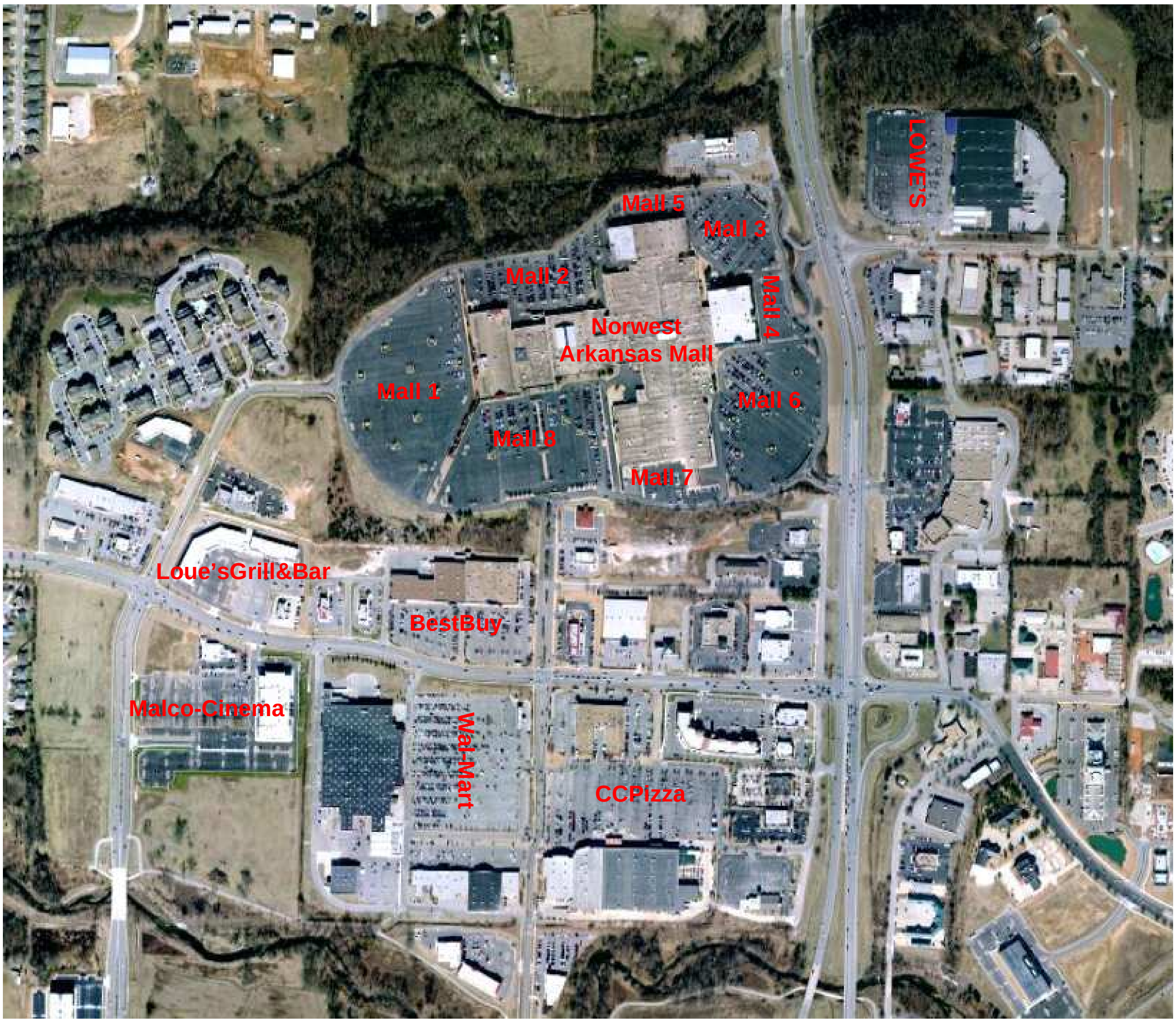


Figure 41. Parking lots Layout

- Evacuation time analysis for different parking rows in Wal-Mart

To further explore the details in parking lots, it is necessary to obtain evacuation time patterns for each parking row. In the project, we only consider the parking rows in Wal-Mart. Based on the design of parking lot layout at Wal-Mart, there are three parking rows: parking row 1 is the closet to the entrance of Wal-Mart, parking row 3 is the farthest to the entrance, and parking row 2 is in the middle. For each parking row, evacuation time may be different.

- Evacuation time distribution across different destinations

This measure is to calculate the time taken for a vehicle to arrive to a safe zone. It therefore can indicate which safe zone is the best for a vehicle to escape to, given a limited evacuation time.

- Total arrival time

Arrival time is different from evacuation time. It is the time at which a vehicle arrives at a safe zone. Based on the CDF plot of the total arrival time distribution, we can estimate what percentage of evacuees is able to successfully escape to safe zones given a certain time period.

- Traffic bottleneck location analysis

Evacuation always occurs along with massive movements of resources and people. It is inevitable that traffic congestion happen. Therefore, the identification of traffic bottlenecks is an important aspect in the emergency planning.

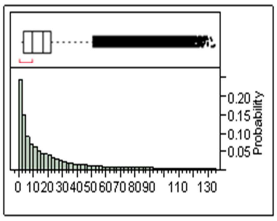
The details of simulation results analysis for each evacuation scenario are summarized in the following subsections.

Evacuation Scenario 1

1) Total evacuation time analysis

Based on **Figure 42**, the mean evacuation time is 15.996 minutes with maximum 134.73 minutes across all parking lots. In addition, we can also summarize the cumulative density function for the evacuation time. For instance, 90% of evacuees have evacuated from parking lots after 100 minutes from beginning of the evacuation.

Evacuation Time Distribution



Quantiles

100.0%	maximum	134.73
99.5%		103.41
97.5%		75.08
90.0%		41.00
75.0%	quartile	21.73
50.0%	median	8.47
25.0%	quartile	2.62
10.0%		1.28
2.5%		0.72
0.5%		0.52
0.0%	minimum	0.23

Moments

Mean	15.995965
Std Dev	19.608451
Std Err Mean	0.0647084
Upper 95% Mean	16.122793
Lower 95% Mean	15.869137
N	91826

CDF Plot

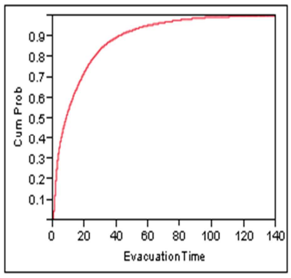


Figure 42. Total Evacuation Time Analysis in Scenario 1

2) Total evacuation time distribution for different parking lots

The average evacuation time for the key parking lots in the study region is illustrated in **Figure 43**. Malco Cinema shown in **Figure 41** has the largest evacuation time of about 34 minutes. The parking lots in Northwest Arkansas Mall have almost the same evacuation time of about 10 minutes.

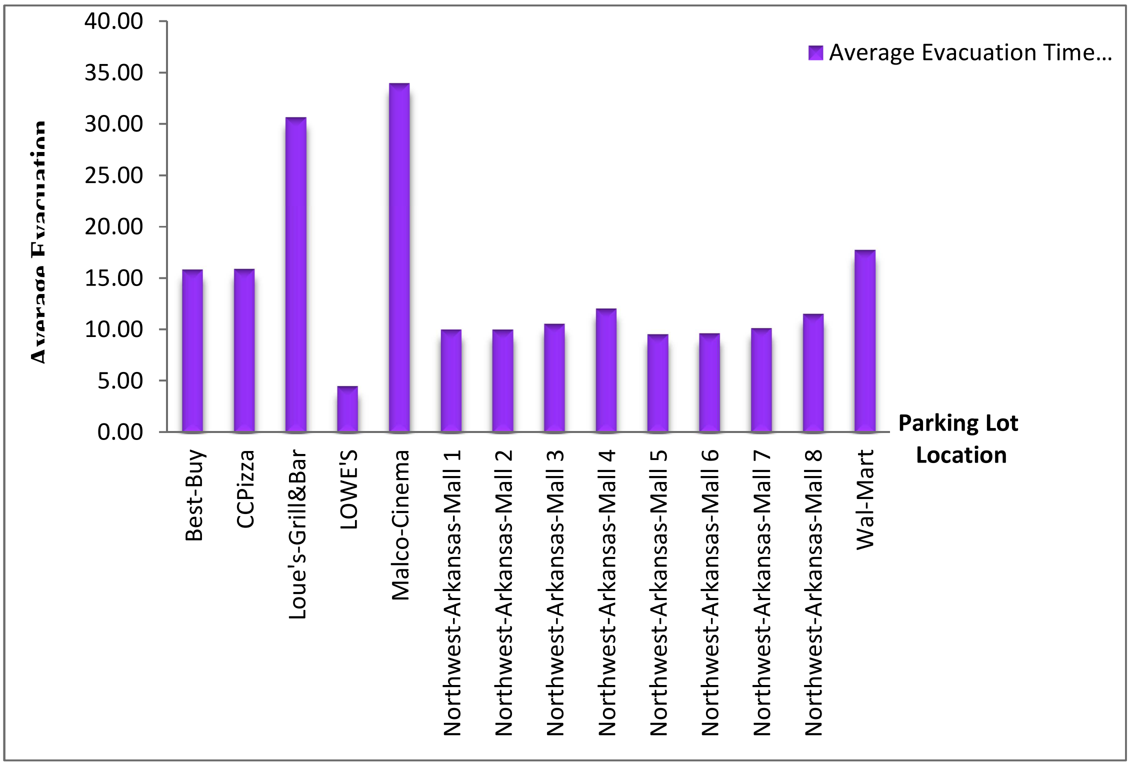


Figure 43. Time to Evacuate Each Parking lot in Scenario 1

3) Evacuation time distribution for different parking rows in Wal-Mart

Based on the **Table 6**, the average evacuation time of parking row 3 is 33.274 and is the maximum among the three parking rows, which seems unreasonable since the parking row 3 is the closet to exits of parking lots. After closer examination of the evacuation distribution of the parking row 3, we can find that only few vehicles evacuated from parking row 3. Thus, it is possible that average evacuation time for parking row 3 can be higher than ones in parking row 1 and parking row2. In sum, there is no obvious difference of evacuation time across parking rows, by ignoring the effects of evacuation time from the parking row 3.

Table 6. Average Evacuation Time for Each Parking Row in Scenario 1

Parking Row #	Avg EvaTime	Max EvaTime	Min EvaTime
Parking row 1	17.9688821	124.52	0.5
Parking row 2	17.044655	123.42	0.5
Parking row 3	33.274	53.68	19.45

4) Evacuation time distributions across different destinations

According to the Figure 44, the minimum evacuation time is 8.178 minutes with destination 372 shown in **Figure 29**. This indicates that it took the least amount of time on average to evacuate to destination 372.

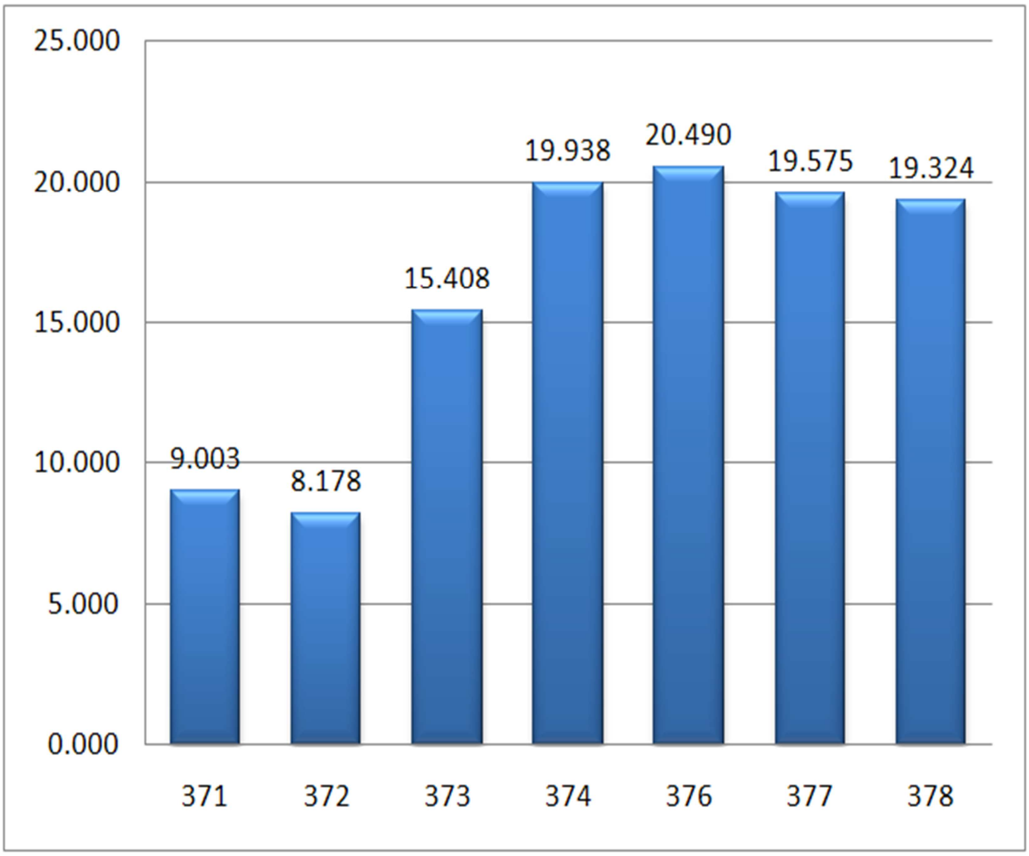
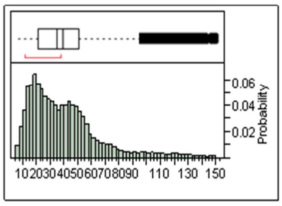


Figure 44. Average Evacuation Times Comparison across Different Destinations in Scenario 1

5) Total Arrival Time Distribution

The arrival time distribution is shown in **Figure 45**. Based on the figure, we can estimate that the percentage of evacuees who are able to escape to safe zones within a time period. For example, about 50% of evacuees can escape to safe zones after 40 minutes from the beginning of the evacuation.

Evacuation Time Distribution



Quantiles

100.0%	maximum	149.77
99.5%		130.40
97.5%		106.20
90.0%		68.22
75.0%	quartile	49.93
50.0%	median	34.02
25.0%	quartile	20.57
10.0%		14.08
2.5%		9.46
0.5%		6.98
0.0%	minimum	5.50

Moments

Mean	38.685183
Std Dev	23.916847
Std Err Mean	0.0789262
Upper 95% Mean	38.839878
Lower 95% Mean	38.530489
N	91826

CDF Plot

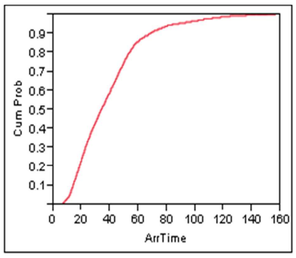


Figure 45. Total Arrival Time Distribution in Scenario 1

6) The traffic bottlenecks over all links within the affected region

By observing the animation of simulation runs, we can identify the key locations where traffic congestion occurs. For example, the situation of traffic congestion in the study region at time 16:50 is shown in **Figure 46**. The bigger that the yellow circle is, the more vehicles are congested. Among the traffic bottlenecks of A, B, C, and D, locations A and D are the most important for evacuation traffic. The detail analysis for evacuation scenario 1 is tabulated in Appendix B1.

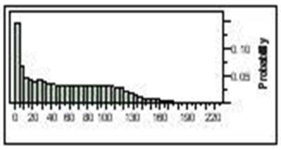
Figure 46. Traffic Bottlenecks in Study Region in Scenario 1

Evacuation Scenario 2

1) Total evacuation time analysis

Based on **Figure 47**, the mean evacuation time is about 55.35 minutes with maximum 220.40 minutes across the parking lots. It is obvious that the average evacuation time is bigger than one obtained in scenario 1, because the probability of traffic congestion is increased due to the increased occupancy rate (85%).

Evacuation Time Distribution



Quantiles

100.0%	maximum	220.40
99.5%		167.01
97.5%		140.43
90.0%		116.93
75.0%	quartile	90.45
50.0%	median	48.65
25.0%	quartile	14.70
10.0%		3.00
2.5%		1.03
0.5%		0.62
0.0%	minimum	0.23

Moments

Mean	55.354346
Std Dev	43.535823
Std Err Mean	0.0952245
Upper 95% Mean	55.540984
Lower 95% Mean	55.167709
N	209024

CDF Plot

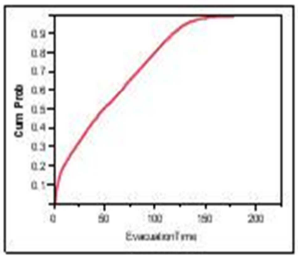


Figure 47. Total Evacuation Time Analysis in Scenario 2

2) Total evacuation time distribution for different parking lots

The average evacuation time for the key parking lots in the study region is illustrated in **Figure 48**. The maximum of evacuation times occur among CC Pizza, Malco Cinema, Northwest Arkansas Mall 3, and Northwest Arkansas Mall 8 shown in **Figure 41**, where traffic congestion happens frequently.

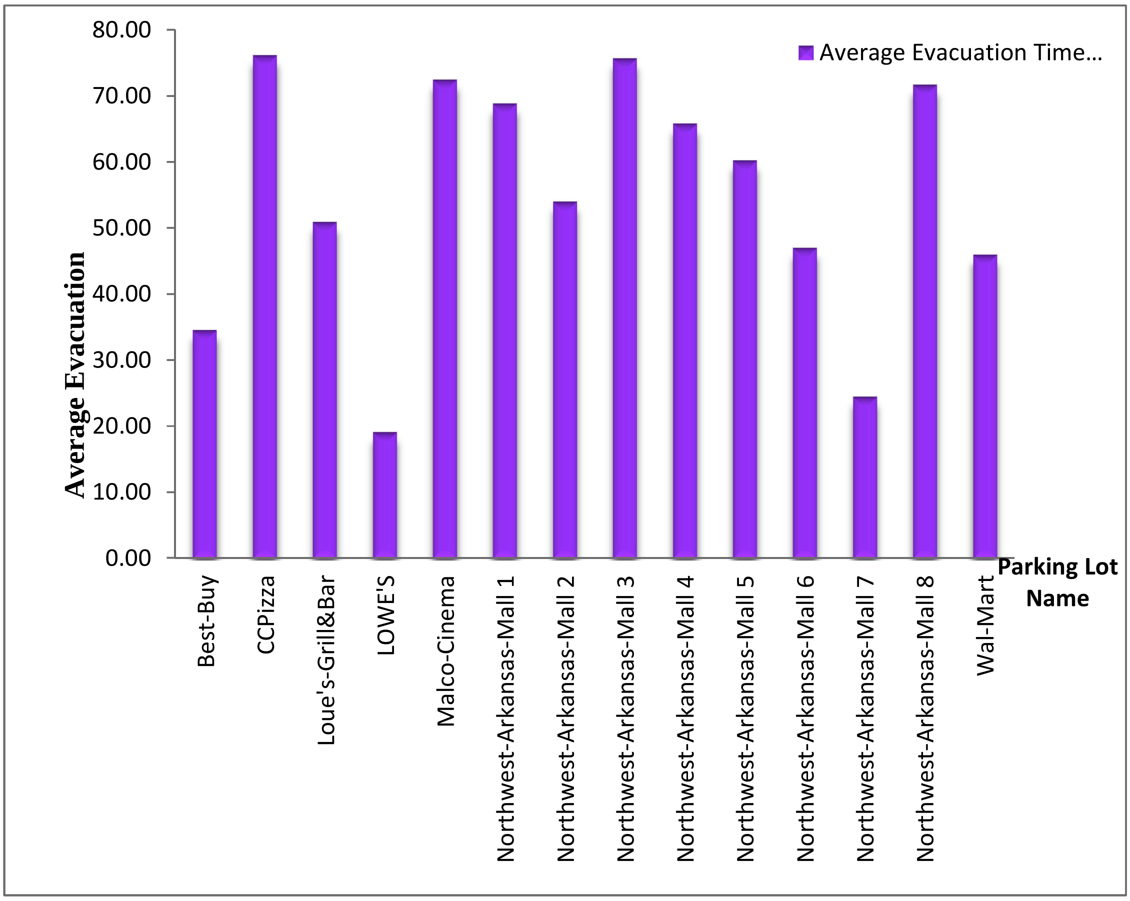


Figure 48. Time to Evacuate Each Parking lot in Scenario 2

3) Evacuation time distribution for different parking rows in Wal-Mart

Based on **Table 7**, the average evacuation time for three parking rows is almost the same at about 46 minutes on average.

Table 7. Average Evacuation Time for Each Parking Row in Scenario 2

Parking Row #	Avg EvaTime	Max EvaTime	Min EvaTime
Parking row 1	46.865	154.72	0.5
Parking row 2	45.403	160.17	0.47
Parking row 3	45.618	145.57	0.4

4) Evacuation time distributions across different destinations

According to **Figure 49** and, the minimum evacuation time is 47.65 minutes with destination 372. This indicates that the destination 372 has the lowest time for vehicles that select it as their destination. The safe zone corresponding to the maximal evacuation time of 62.06 minutes is zone 376 shown in **Figure 29**.

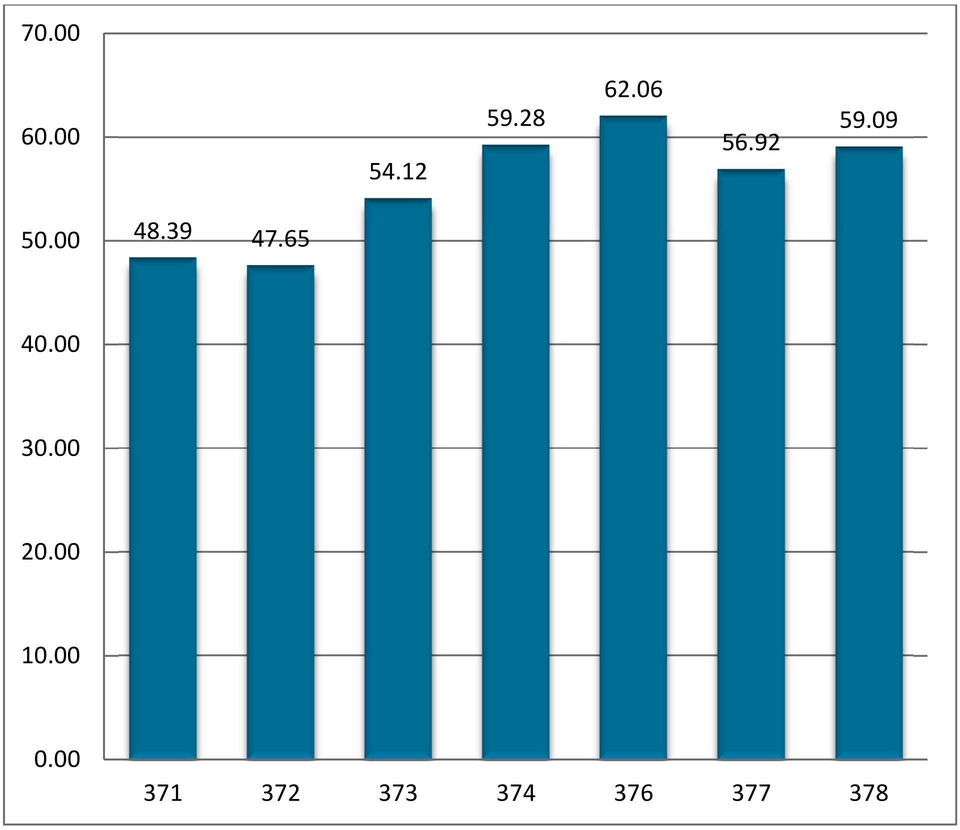
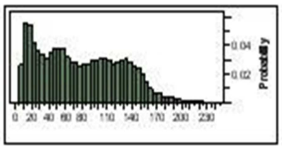


Figure 49. Average Evacuation Times Comparison across Different Destinations in Scenario 2

5) Total Arrival Time Distribution

The arrival time distribution is shown in **Figure 50**. Based on the figure, about 50% of evacuees arrive to a safe zone within 75 minutes of the beginning of an evacuation.

Evacuation Time Distribution



Quantiles

100.0%	maximum	239.92
99.5%		194.88
97.5%		167.30
90.0%		143.93
75.0%	quartile	117.05
50.0%	median	73.25
25.0%	quartile	35.88
10.0%		16.63
2.5%		9.83
0.5%		7.13
0.0%	minimum	5.40

Moments

Mean	78.044303
Std Dev	47.750137
Std Err Mean	0.1044423
Upper 95% Mean	78.249007
Lower 95% Mean	77.839598
N	209024

CDF Plot

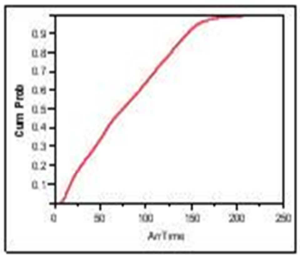


Figure 50. Total Arrival Time Distribution in Scenario 2

6) The Traffic bottlenecks over all links within the affected region

In this scenario, there are many traffic bottlenecks during evacuation as shown in **Figure 51**. Most of traffic gridlock happens at the exits connecting the main roads inside of the parking lots. For example, the traffic situation at 16:50 is illustrated in **Figure 51**, where major congestion occurs at road A, road B, road C and road D. The traffic congestion at the road A is the most important for reducing entire evacuation traffic, because it causes serious traffic congestion at the intersection of N College Ave and E Joyce Blvd, which in turn causes the traffic congestion at other locations. The detail analysis for evacuation scenario 2 is tabulated in Appendix B2.

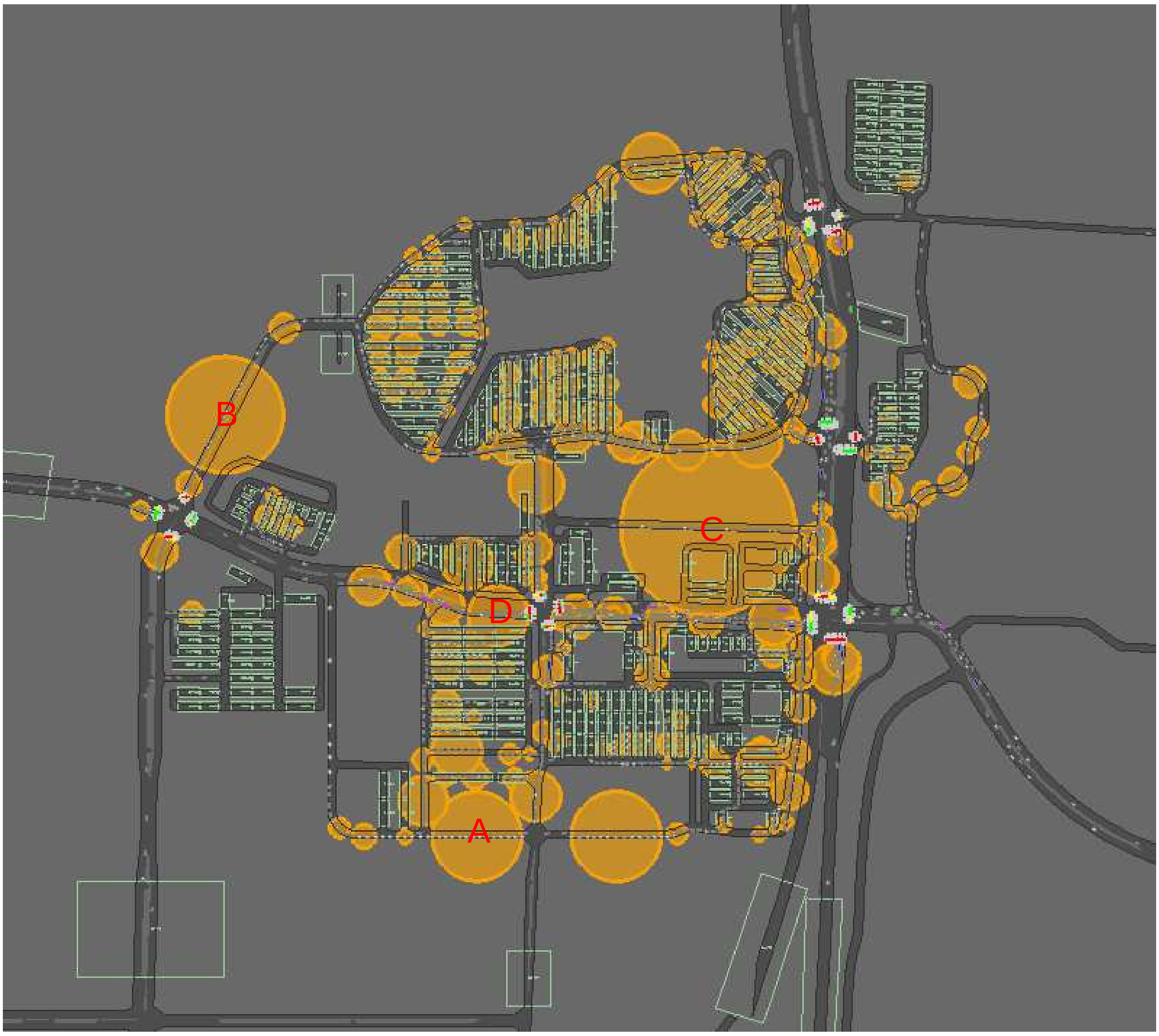


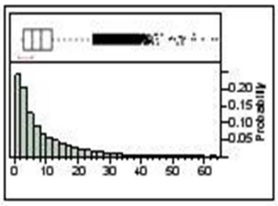
Figure 51. Traffic Bottlenecks in Study Region in Scenario 2

Evacuation Scenario 3

1) Total evacuation time analysis

Based on **Figure 52**, the mean evacuation time is 7.746 minutes with maximum 63.42 minutes across the parking lots. Fifty percent of the evacuees have evacuated from parking lots after 5 minutes from the beginning of the evacuation.

Evacuation Time Distribution



Quantiles

100.0%	maximum	63.420
99.5%		34.530
97.5%		28.480
90.0%		19.100
75.0%	quartile	11.030
50.0%	median	4.880
25.0%	quartile	2.080
10.0%		1.150
2.5%		0.680
0.5%		0.500
0.0%	minimum	0.250

Moments

Mean	7.7459907
Std Dev	7.5930467
Std Err Mean	0.0250152
Upper 95% Mean	7.7950202
Lower 95% Mean	7.6969612
N	92135

CDF Plot

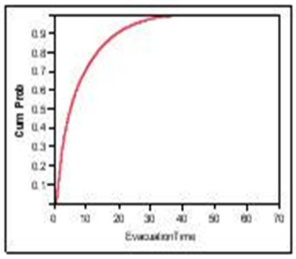


Figure 52. Total Evacuation Time Analysis in Scenario 3

2) Total evacuation time distribution for different parking lots

The average evacuation time for the key parking lots in the study region is illustrated in **Figure 53**. The maximum evacuation time occurs among Loue's Grill & Bar, Malco Cinema, and War-Mart, which is shown in **Figure 41**.

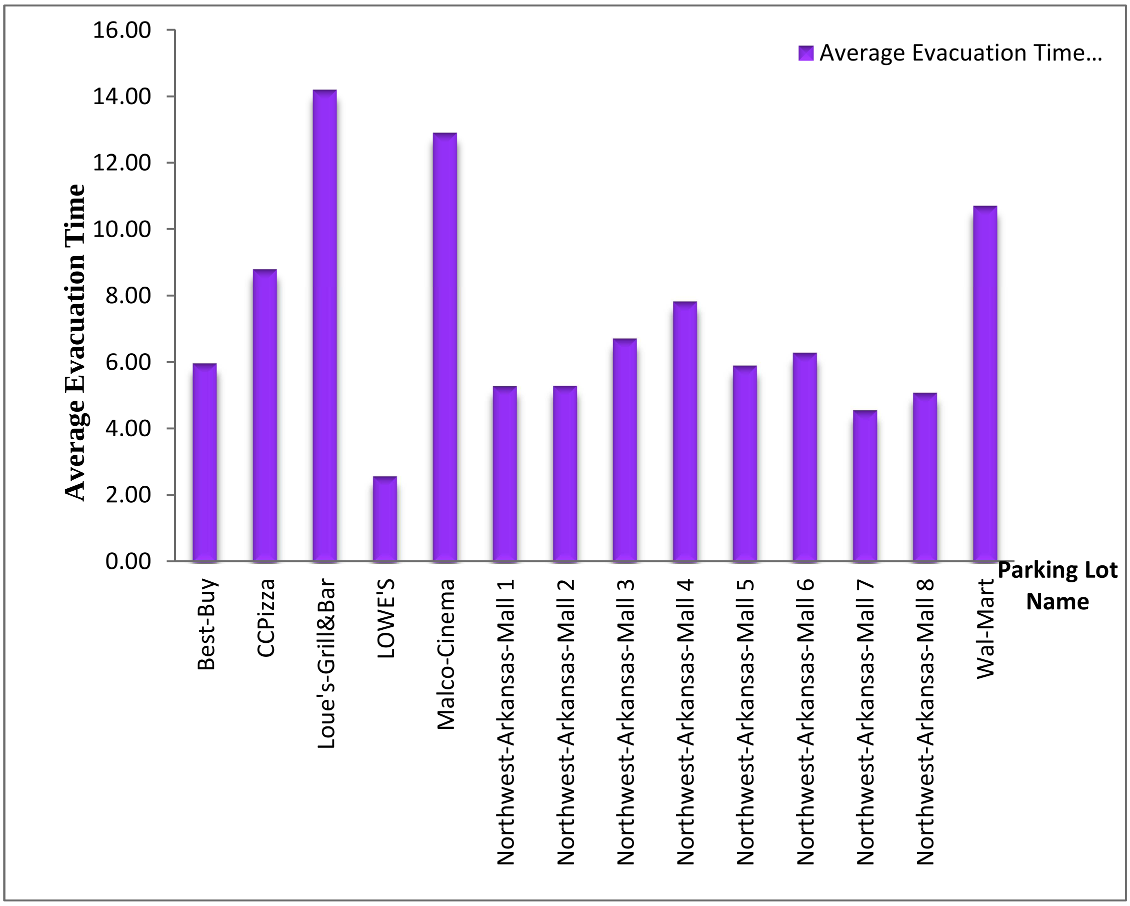


Figure 53. Time to Evacuate Each Parking lot in Scenario 3

3) Evacuation time distribution for different parking rows in Wal-Mart

Based on the **Table 8**, the maximum of the average evacuation time among the three parking rows is 18.33 minutes in parking row 3. This indicates that vehicles generated in parking row 3 wait longer on average to evacuate.

Table 8. Average Evacuation Time for Each Parking Row in Scenario 3

Parking Row #	Avg EvaTime	Max EvaTime	Min EvaTime
Parking row 1	10.79	55.58	0.48
Parking row 2	10.48	40.37	0.48
Parking row 3	18.33	28.78	9.23

4) Evacuation time distributions across different destinations

According to the Figure 54, the minimum evacuation time is 3.9 minutes with destination 371. This indicates the destination 371 has the quickest time to evacuation. The worst safe zone corresponding to maximal evacuation time of 10.2 minutes is zone 377 shown in Figure 29.

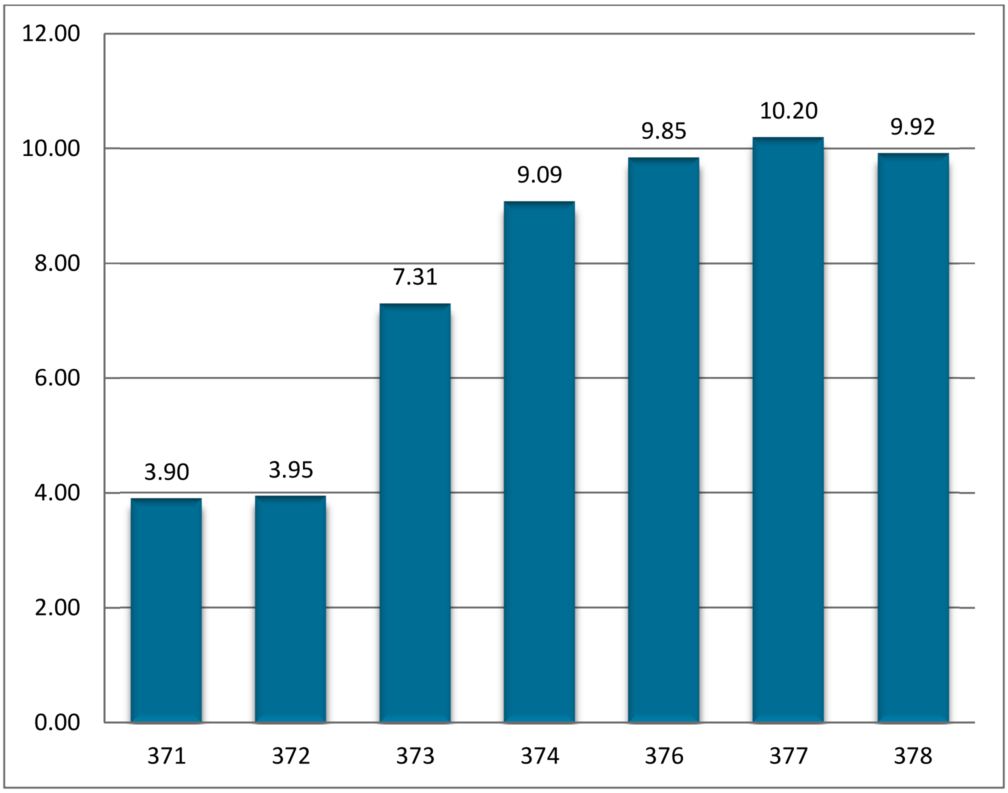
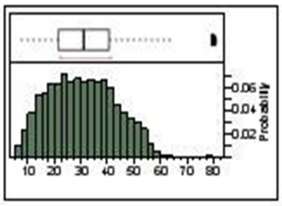


Figure 54. Average Evacuation Times Comparison across Different Destinations in Scenario 3

5) Total Arrival Time Distribution

The arrival time distribution is shown in **Figure 55**. Based on the figure, about 50% of the evacuees can arrive to a safe zone after 30 minutes.

Evacuation Time Distribution



Quantiles

100.0%	maximum	79.900
99.5%		57.080
97.5%		54.350
90.0%		47.580
75.0%	quartile	39.700
50.0%	median	30.080
25.0%	quartile	20.620
10.0%		14.080
2.5%		9.370
0.5%		6.964
0.0%	minimum	5.420

Moments

Mean	30.436642
Std Dev	12.322864
Std Err Mean	0.0405975
Upper 95% Mean	30.516212
Lower 95% Mean	30.357071
N	92135

CDF Plot

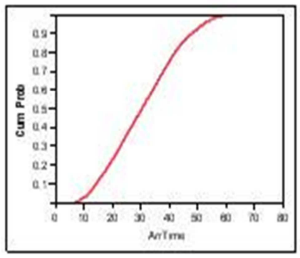


Figure 55. Total Arrival Time Distribution in Scenario 3

6) The Traffic bottlenecks over all links within the affected region

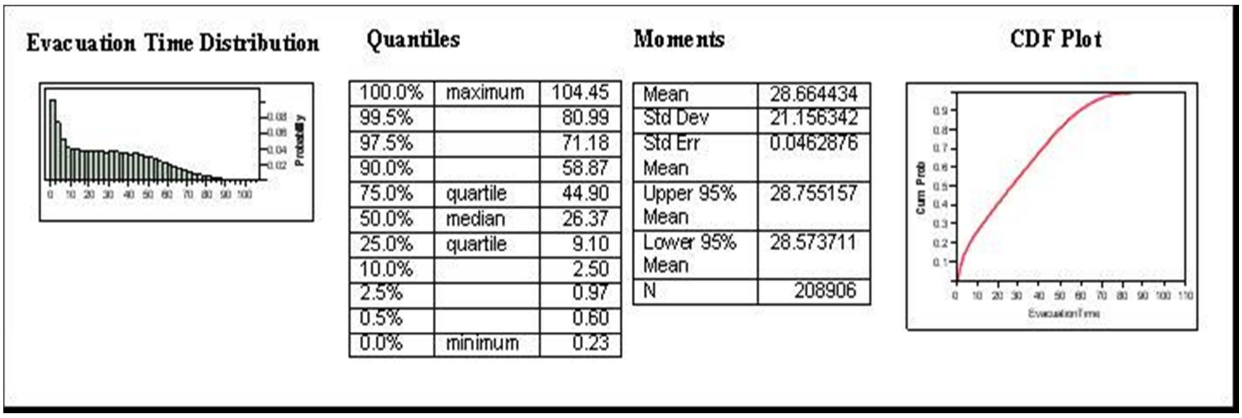
The key location where traffic congestion occurs at time 16:50 is shown in **Figure 56**, where traffic is primarily congested at main evacuation routes. Overall there is less congestion in this scenario. The roads A and C are the key roads for reducing overall traffic congestion, because the traffic gridlock at these two roads leads to traffic congestion at the intersection of N College Ave and E Joyce Blvd, which in turn cause the traffic congestion at other locations.

Figure 56. Traffic Bottlenecks in Study Region in Scenario 3

Evacuation Scenario 4

1) Total evacuation time analysis

Based on **Figure 57**, the mean evacuation time is 28.664 minutes with maximum 104.45 minutes across all parking lots. In addition, 50% of evacuees have evacuated from parking lots after 26 minutes.



100.0%	maximum	104.45
99.5%		80.99
97.5%		71.18
90.0%		58.87
75.0%	quartile	44.90
50.0%	median	26.37
25.0%	quartile	9.10
10.0%		2.50
2.5%		0.97
0.5%		0.60
0.0%	minimum	0.23

Mean	28.664434
Std Dev	21.156342
Std Err Mean	0.0462876
Upper 95% Mean	28.755157
Lower 95% Mean	28.573711
N	208906

Figure 57. Total Evacuation Time Analysis in Scenario 4

2) Total evacuation time distribution for different parking lots

The average evacuation time for the key parking lots in the study region is illustrated in **Figure 58**. The maximum of evacuation time occurs among Loue's Grill & Bar and Malco Cinema shown in **Figure 41**.

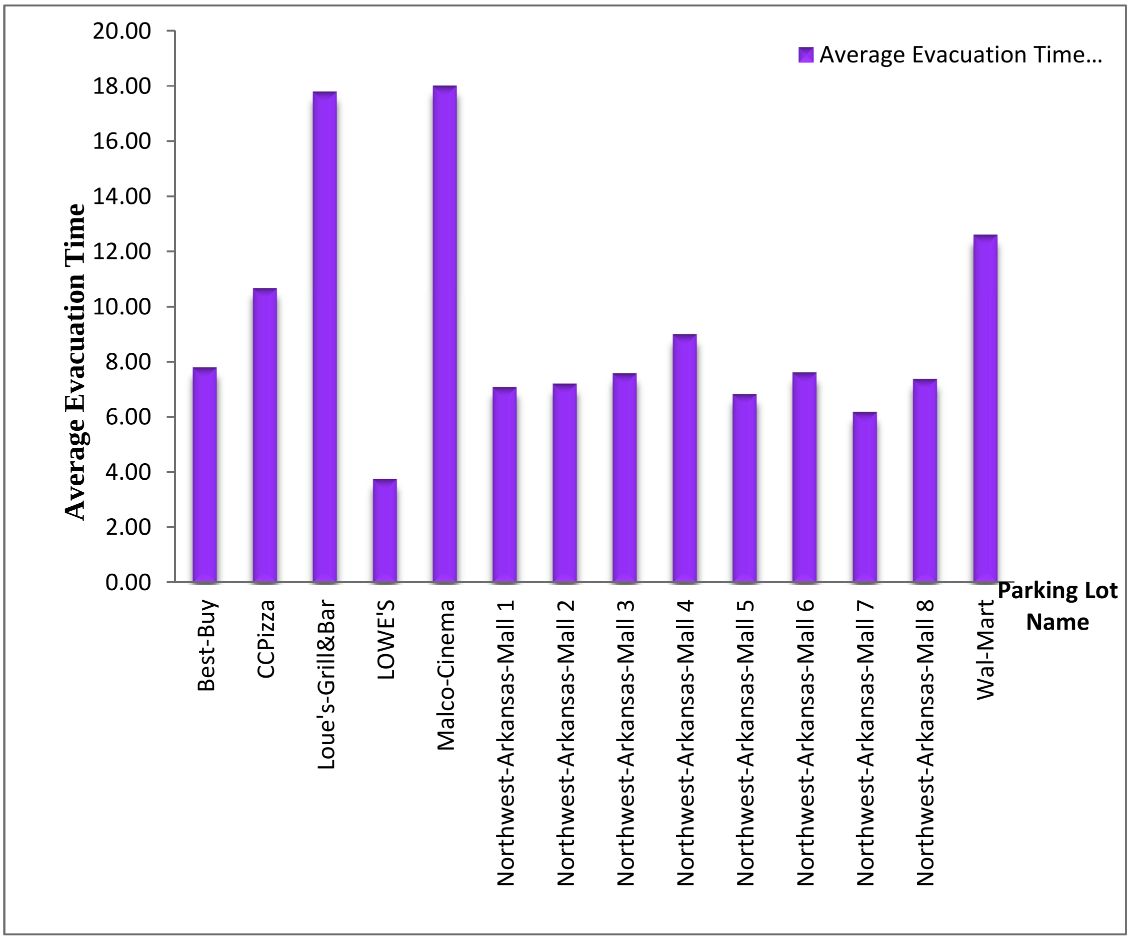


Figure 58. Time to Evacuate Each Parking lot in Scenario 4

3) Evacuation time distribution for different parking rows in Wal-Mart

Based on the **Table 9**, the average evacuation time for three parking rows is almost the same at about 31 minutes on average.

Table 9. Average Evacuation Time for Each Parking Row in Scenario 4

Parking Row #	Avg EvaTime	Max EvaTime	Min EvaTime
Parking row 1	31.47	77.45	0.52
Parking row 2	30.81	79.48	0.45
Parking row 3	30.55	74.97	0.37

4) Evacuation time distributions across different destinations

According to the **Figure 59**, the minimum evacuation time is 24.80 minutes with destination 371 shown in **Figure 29**.

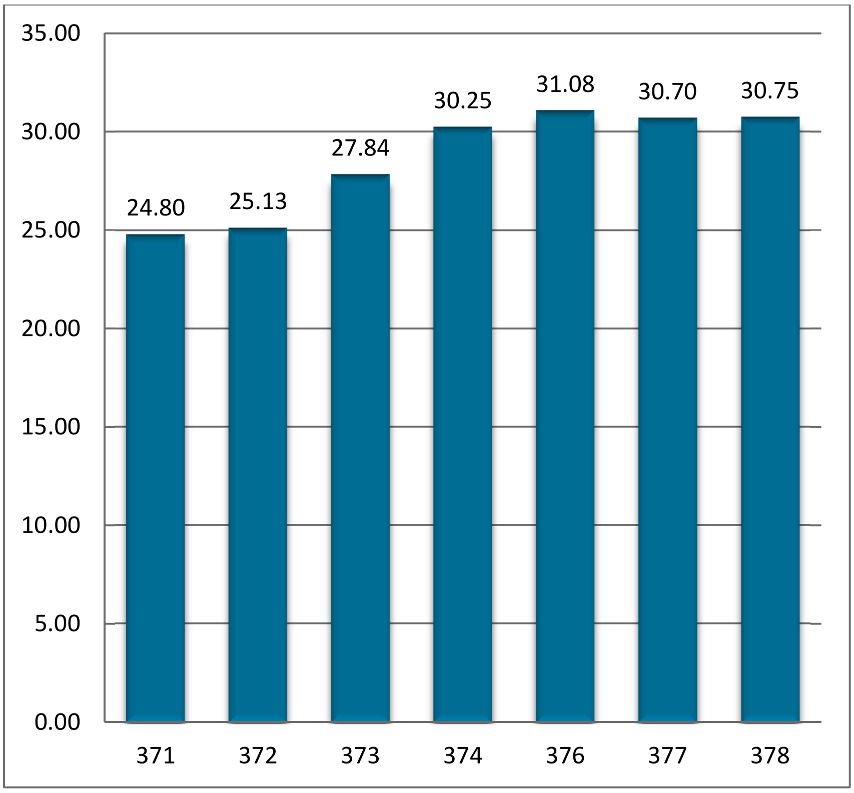
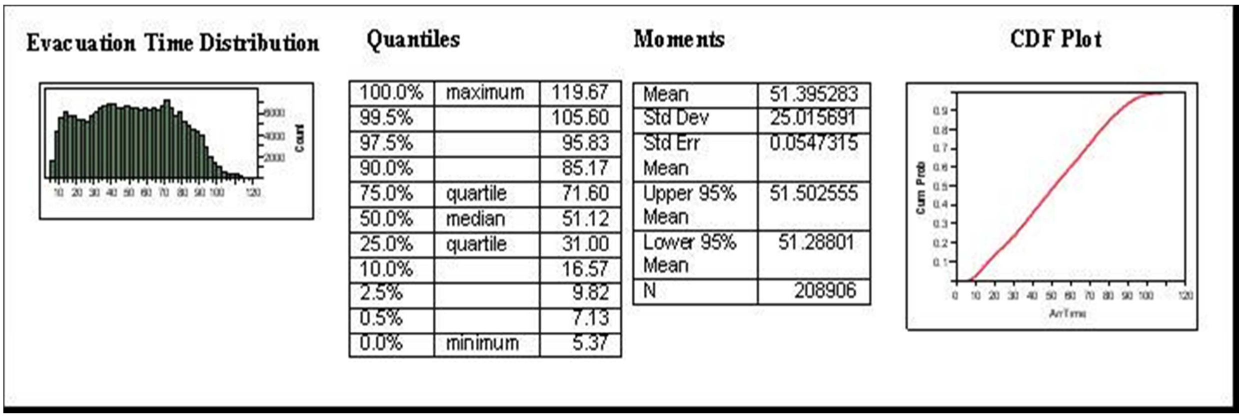


Figure 59. Average Evacuation Times Comparison across Different Destinations in Scenario 4

5) Total Arrival Time Distribution

The arrival time distribution is shown in **Figure 60**. Based on the figure, about 50% of evacuees could escape to safe zones after 51 minutes.



Evacuation Time Distribution

Quantiles

100.0%	maximum	119.67
99.5%		105.60
97.5%		95.83
90.0%		85.17
75.0%	quartile	71.60
50.0%	median	51.12
25.0%	quartile	31.00
10.0%		16.57
2.5%		9.82
0.5%		7.13
0.0%	minimum	5.37

Moments

Mean	51.395283
Std Dev	25.015691
Std Err Mean	0.0547315
Upper 95% Mean	51.502555
Lower 95% Mean	51.28801
N	208906

CDF Plot

Figure 60. Total Arrival Time Distribution in Scenario 4

6) The Traffic bottlenecks over all links within affected region

By observing the animation of simulation runs, we can identify the key locations where traffic congestion occurs as shown in **Figure 61**. The bigger the yellow circle, the more traffic congestion occurs. For example, there are four major traffic bottlenecks: A, B, C, and D, in which traffic congestion on roads A and B are the most important and they cause the most of congestion in the study region.

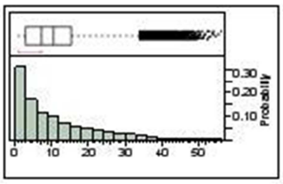
Figure 61. Traffic Bottlenecks in Study Region in Scenario 4

Evacuation Scenario 5

1) Total evacuation time analysis

Based on **Figure 62**, the mean evacuation time is 10 minutes with maximum 55.82 minutes across all parking lots. 50% of evacuees have evacuated from parking lots after 7 minutes.

Evacuation Time Distribution



Quantiles

100.0%	maximum	55.820
99.5%		40.880
97.5%		34.470
90.0%		24.930
75.0%	quartile	14.830
50.0%	median	6.650
25.0%	quartile	2.420
10.0%		1.270
2.5%		0.700
0.5%		0.520
0.0%	minimum	0.250

Moments

Mean	10.020729
Std Dev	9.5737401
Std Err Mean	0.0315903
Upper 95% Mean	10.082645
Lower 95% Mean	9.9588118
N	91845

CDF Plot

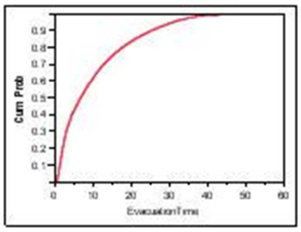


Figure 62. Total Evacuation Time Analysis in Scenario 5

2) Total evacuation time distribution for different parking lots

The average evacuation time for the key parking lots in the study region is illustrated in **Figure 63**. The maximum of evacuation times occurs among Loue's Grill & Bar and Malco Cinema shown in **Figure 41**.

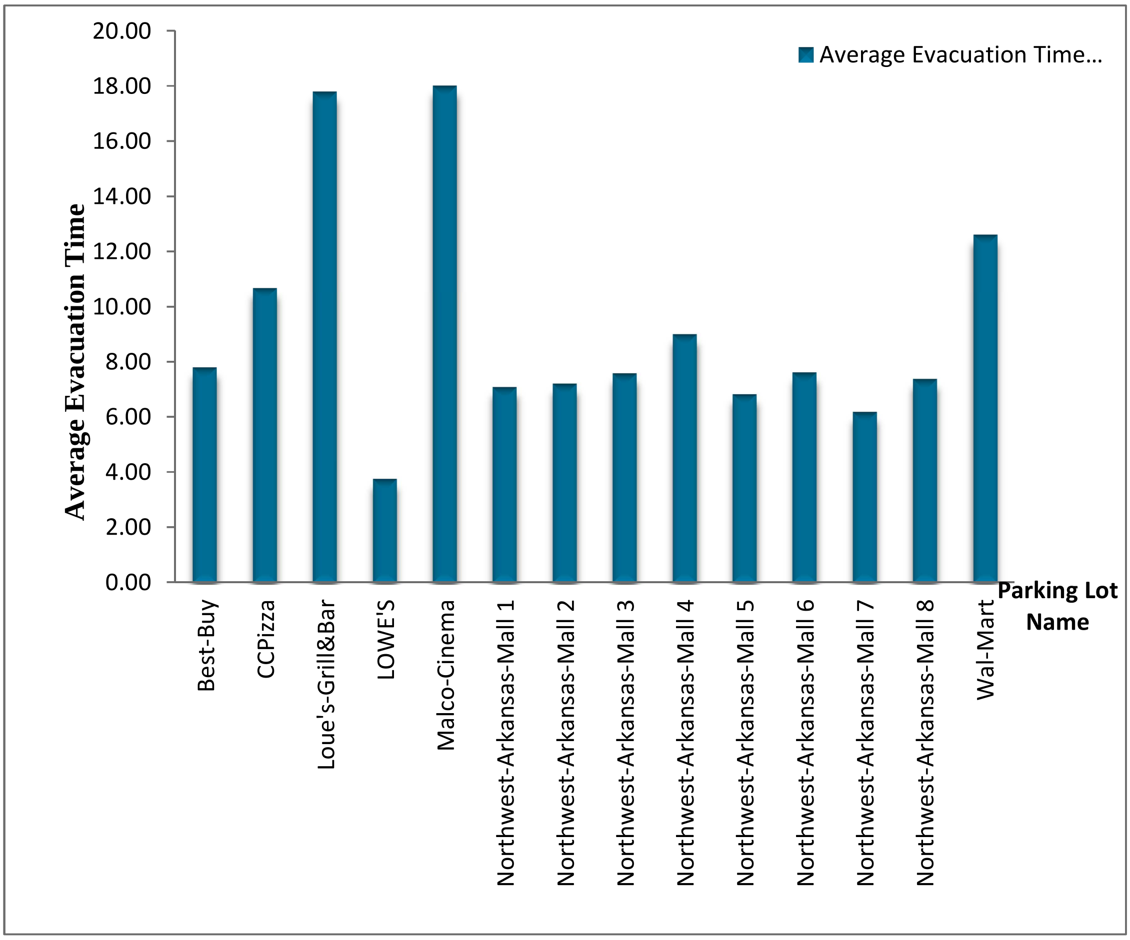


Figure 63. Time to Evacuate Each Parking lot in Scenario 5 in Scenario 5

3) Evacuation time distribution for different parking rows in Wal-Mart

Based on the **Table 10**, the average evacuation time of the parking row 3 is 17.98 and is the maximum among the three parking rows.

Table 10. Average Evacuation Time for Each Parking Row in Scenario 5

Parking Row #	Avg EvaTime	Max EvaTime	Min EvaTime
Parking row 1	12.63	52.33	0.48
Parking row 2	12.63	54.07	0.50
Parking row 3	17.98	35.67	3.15

4) Evacuation time distributions across different destinations

According to **Figure 64**, the minimum evacuation time is 5.64 minutes with destination 372 shown in **Figure 29**.

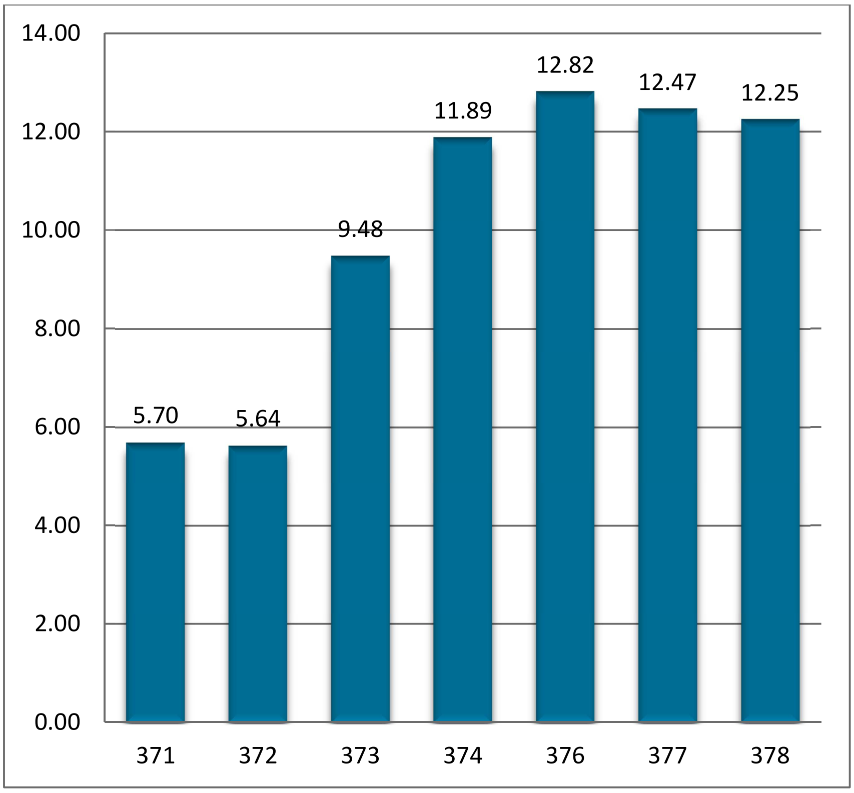
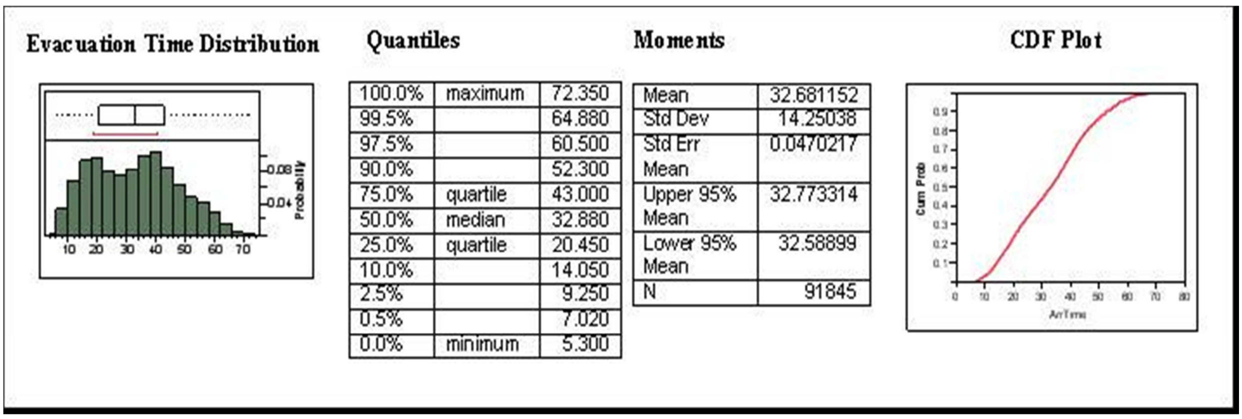


Figure 64. Average Evacuation Times Comparison across Different Destinations in Scenario 5

5) Total Arrival Time Distribution

The arrival time distribution is shown in **Figure 65**. Based on the figure, about 50% of evacuees can escape to safe zones after 32 minutes.



100.0%	maximum	72.350
99.5%		64.880
97.5%		60.500
90.0%		52.300
75.0%	quartile	43.000
50.0%	median	32.880
25.0%	quartile	20.450
10.0%		14.050
2.5%		9.250
0.5%		7.020
0.0%	minimum	5.300

Mean	32.681152
Std Dev	14.25038
Std Err Mean	0.0470217
Upper 95% Mean	32.773314
Lower 95% Mean	32.58899
N	91845

Figure 65. Total Arrival Time Distribution in Scenario 5

6) The Traffic bottlenecks over all links within the affected region

The key locations where traffic congestion occurs are shown in **Figure 66.** The major congestion events happen on the roads around Wal-Mart. The congestion at location A is the most important, because it causes the traffic congestion at locations B and D.

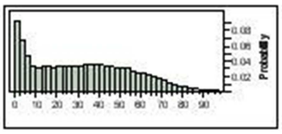
Figure 66. Traffic Bottlenecks in Study Region in Scenario 5

Evacuation Scenario 6

1) Total evacuation time analysis

Based on **Figure 67**, the mean evacuation time is 31.88 minutes with a maximum 97.02 minutes across all parking lots. Fifty percent of evacuees have evacuated from parking lots after 31minutes.

Evacuation Time Distribution



Quantiles

100.0%	maximum	97.020
99.5%		84.600
97.5%		75.550
90.0%		63.230
75.0%	quartile	49.380
50.0%	median	30.630
25.0%	quartile	11.170
10.0%		2.780
2.5%		1.000
0.5%		0.600
0.0%	minimum	0.230

Moments

Mean	31.880702
Std Dev	22.418596
Std Err Mean	0.0490833
Upper 95% Mean	31.976905
Lower 95% Mean	31.7845
N	208617

CDF Plot

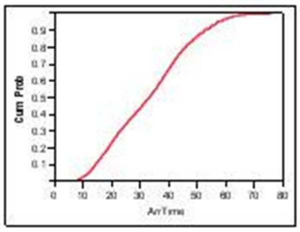


Figure 67. Total Evacuation Time Analysis in Scenario 6

2) Total evacuation time distribution for different parking lots

The average evacuation time for the key parking lots in the study region is illustrated in **Figure 68.** The maximum of evacuation times occur among Loue's Grill & Bar and Northwest Arkansas Mall 4 shown in **Figure 41**.

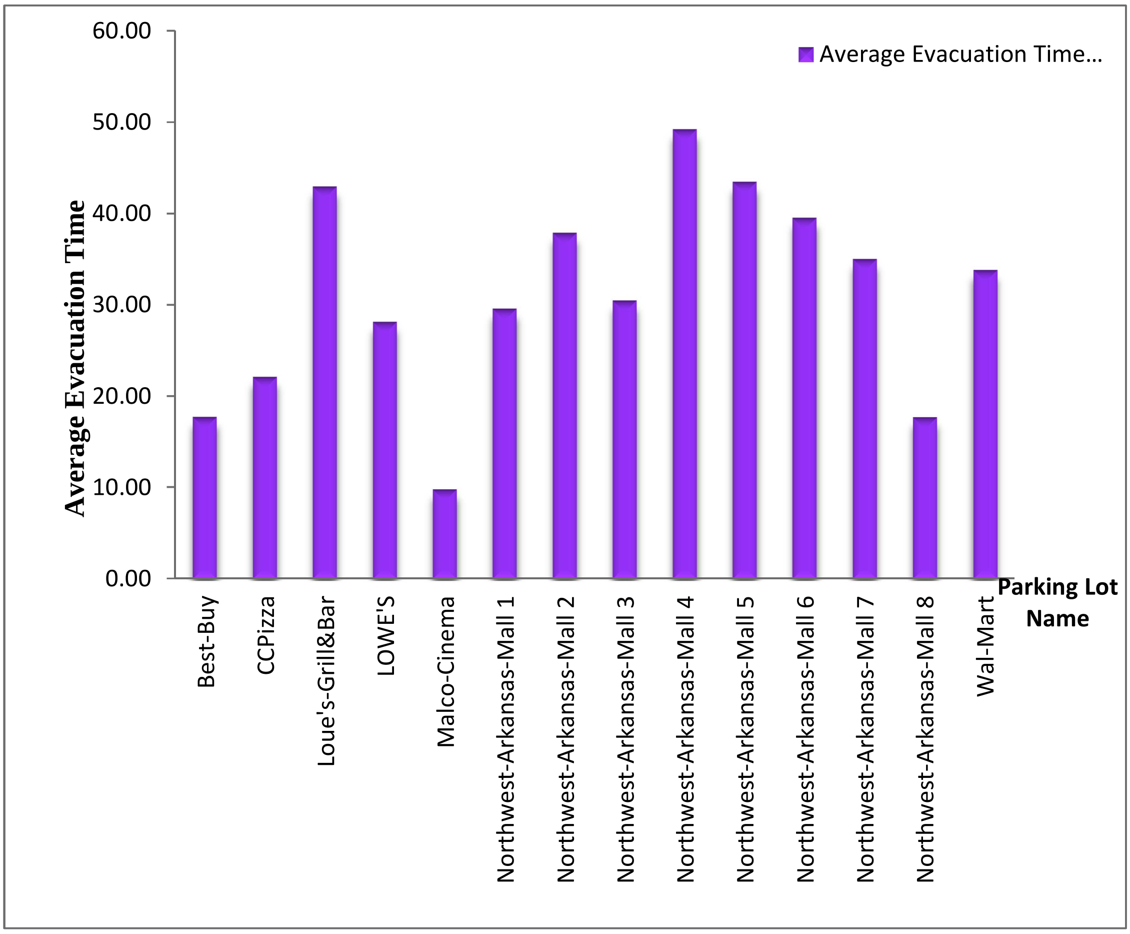


Figure 68. Time to Evacuate Each Parking lot in Scenario 5 in Scenario 6

3) Evacuation time distribution for different parking rows in Wal-Mart

Based on **Table 11**, the average evacuation time of parking row 3 is 33 minutes, and there is no obvious time difference among three parking rows.

Table 11. Average Evacuation Time for Each Parking Row in Scenario 6

Parking Row #	Avg EvaTime	Max EvaTime	Min EvaTime
Parking row 1	33.52	90.72	0.5
Parking row 2	32.48	90.97	0.45
Parking row 3	33.75	91.08	0.37

4) Evacuation time distributions across different destinations

According to **Figure 69**, the minimum evacuation time is 27.8 minutes for destination 371. The worst safe zone is 376 with maximal evacuation time of 34.59. The zones are shown in **Figure 29**.

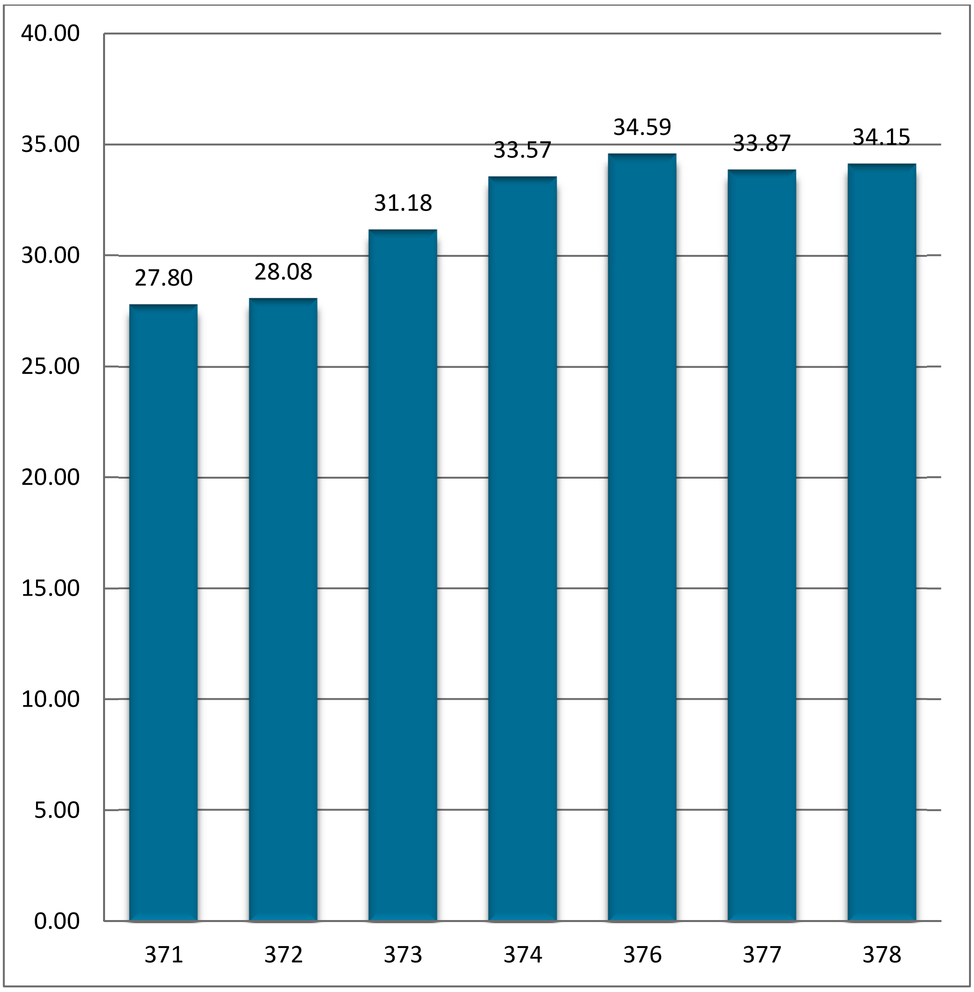
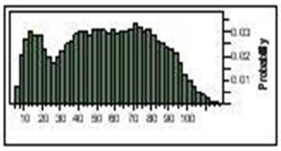


Figure 69. Average Evacuation Times Comparison across Different Destinations in Scenario 6

5) Total Arrival Time Distribution

The arrival time distribution is shown in **Figure 70**. Based on the figure, about 50% of evacuees can escape to safe zones after 55 minutes.

Evacuation Time Distribution



Quantiles

100.0%	maximum	116.88
99.5%		107.95
97.5%		100.28
90.0%		89.83
75.0%	quartile	75.95
50.0%	median	55.35
25.0%	quartile	33.78
10.0%		16.42
2.5%		9.80
0.5%		7.12
0.0%	minimum	5.42

Moments

Mean	54.566304
Std Dev	26.407805
Std Err Mean	0.0578173
Upper 95% Mean	54.679625
Lower 95% Mean	54.452984
N	208617

CDF Plot

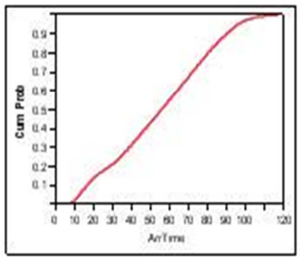


Figure 70. Total Arrival Time Distribution in Scenario 6

6) The Traffic bottlenecks over all links at affected region

The key location where traffic congestion occurs at time 16:50 is shown in **Figure 71**, where the major congestion location are A, B, C and D. The congestions at roads A and B are the most important. The congestion at location C is caused by traffic congestion at N College Ave, which can be relieved if traffic from A and B to N College Ave is reduced.

Figure 71. Traffic Bottlenecks in Study Region in Scenario 6

4.5.3. Overall Analysis and Conclusions

Based on the individual evacuation model scenario results in Section 4.5.2, this section primarily focuses on the simulation results across different scenarios. The details are addressed as follows.

1) Total evacuation time analysis

Evacuation time is prone to numerous factors and it varies by different evacuation scenarios. The general evacuation time analysis for each model scenario is tabulated in Table 12.

Table 12. Evacuation Time analysis across Model Scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
Average Evacuation Time	16.00	55.35	7.75	28.66	10.02	31.88
Maximal Evacuation Time	134.73	220.40	63.42	104.45	55.82	97.02
Minimal Evacuation Time	0.23	0.23	0.25	0.23	0.25	0.23

According to the table, we can summarize the followings results:

- The evacuation time of model scenarios with 85% occupancy rate is greater than model scenarios with normal occupancy rates. Because the former involves much more movement of resources and easily causes much more traffic congestion in the study region. For example, it takes about 55 minutes to evacuate the whole study area in scenario 2; however, it only takes about 16 minutes in scenario 1.
- For each occupancy rate, evacuation time is the smallest in the model with stopped background traffic, and the greatest in the model with the background traffic of the same level. The evacuation time in the model with gradually reduced background traffic is in the middle. Because of less background traffic during evacuation, less interaction occurs between evacuation traffic and background traffic. For example, the

evacuation time gets higher for scenario 2, scenario 6, and scenario 4, where the occupancy rates are 85%.

- The minimal evacuation time is about 0.23 minutes. It is not possible in reality for a driver to escape to safe zones in this of short time. After scrutinizing, the simulation animation and model results, we find that this evacuation time only exists for vehicles generated both in the parking lots close to safe zones and at the beginning of the evacuation when the evacuation traffic is not too much and background traffic congestion is low. Another reason also could explain this short evacuation time. In our model, we do not consider the process of drivers walking out of a building to get their cars in parking lots. In addition, in Paramics, vehicles are generated within zones. When a vehicle is released from a zone, its speed is the same as the link of the zone. Therefore the beginning speed of vehicles is highly determined by the link speed limit. In our model, we assume that the speed is 10 miles/hr for parking lot roads. Therefore, the vehicle's speed in parking lots is about 10 mile/hr at the beginning which is higher than in reality. Based on these factors, it is possible within the model that an evacuation time can be less than 1 minute.

2) Evacuation time distribution for different parking lot

For different parking lots, the evacuation time is not the same. As shown in Figure 72, the maximal evacuation time occurs generally in model scenario 2, due to the fact that there are more vehicles participating in the evacuation than in the other scenarios. For each model scenario, the largest evacuation time generally occurs for the parking lots: CCPizza, Loue's-Grill&Bar, Malco-Cinema, and Northwest Arkansas Mall, because there are more people in these areas especially on the weekends.

Parking Lot Name	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Maximal ETime
Best-Buy	15.84	34.60	6.00	18.37	7.82	17.77	34.60
CCPizza	15.91	76.17	8.82	39.59	10.70	22.15	76.17
Loue's-Grill&Bar	30.65	50.97	14.20	22.27	17.81	42.97	50.97
LOWE'S	4.49	19.19	2.61	6.64	3.78	28.18	28.18
Malco-Cinema	33.97	72.48	12.91	23.88	18.02	9.83	72.48
Northwest-Arkansas-Mall 1	9.97	68.89	5.30	33.92	7.11	29.62	68.89
Northwest-Arkansas-Mall 2	9.96	54.03	5.32	27.81	7.23	37.92	54.03
Northwest-Arkansas-Mall 3	10.55	75.70	6.74	46.70	7.61	30.50	75.70
Northwest-Arkansas-Mall 4	12.04	65.88	7.85	40.14	9.02	49.20	65.88
Northwest-Arkansas-Mall 5	9.51	60.29	5.93	38.08	6.85	43.48	60.29
Northwest-Arkansas-Mall 6	9.59	47.04	6.32	33.39	7.64	39.55	47.04
Northwest-Arkansas-Mall 7	10.13	24.51	4.57	15.49	6.19	35.00	35.00
Northwest-Arkansas-Mall 8	11.52	71.72	5.11	30.49	7.40	17.72	71.72
Wal-Mart	17.73	46.03	10.72	31.00	12.63	33.81	46.03
Maximal ETime	33.97	76.17	14.20	46.70	18.02	49.20	

Figure 72. Evacuation Time of Parking lots across Scenarios

3) Evacuation time distribution for parking rows

For each parking row within a parking lot for Wal-Mart, the average evacuation time is illustrated in Table 13. As discussed in the result analysis of individual evacuation model scenarios in Section 4.5.2, generally there is not much difference for the evacuation time for these parking rows, which may not be reasonable in reality. However, it is explainable in the project. In our simulation model, we model the parking lot in a simplified method, not considering the behaviors of pedestrians and vehicles in more detail. For example, we consider the procedure that drivers get in their car, drive out parking lots and escape to safe zones, however we ignore the process of how drivers get out of buildings and find their cars in parking lots, which can affect evacuation time greatly. Without considering the detailed movements in parking lots, the evacuation time for different parking rows may not be very different. This suggests that the detailed modeling of the movements within parking lots during an evacuation is an important area for future research. We are unaware of any commercial off the shelf traffic modeling programs that can effectively model this situation.

Table 13. Average Evacuation Time for Parking rows across Scenarios

Parking row #	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
Parking row 1	17.97	46.87	10.79	31.47	12.63	33.52
Parking row 2	17.04	45.40	10.48	30.81	12.63	32.48
Parking row 3	33.27	45.62	18.33	30.55	17.98	33.75

4) Evacuation time distributions for different destinations

The average evacuation time for each destination in different scenarios is provided in **Table 14.** Based on the table, we can find that 371 and 372 are the best safe zones for evacuees, which require the least evacuation time. According to the map of study region and simulation runs, we find that 371 and 372 are not only closer to shopping areas but also suffer from lower traffic congestion.

Table 14. Average Evacuation Time for Destinations across Scenarios

Destination #	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
371	9.00	48.39	3.90	24.80	5.70	27.80
372	8.18	47.65	3.95	25.13	5.64	28.08
373	15.41	54.12	7.31	27.84	9.48	31.18
374	19.94	59.28	9.09	30.25	11.89	33.57
376	20.49	62.06	9.85	31.08	12.82	34.59
377	19.58	56.92	10.20	30.70	12.47	33.87
378	19.32	59.09	9.92	30.75	12.25	34.15
Minimal ETime	8.18	47.65	3.90	24.80	5.64	27.80
Maximal Etime	20.49	62.06	10.20	31.08	12.82	34.59

5. Summary

In this exploratory research, we have addressed the general procedure of modeling evacuation in a large shopping district from modeling assumptions to model construction, model scenario development, and experiments. We have successfully applied the modeling methodologies to a case study in the region around the Northwest Arkansas Mall at Fayetteville, AR; however, we have encountered many challenges concerning modeling issues and there are still several areas open for future studies.

5.1. Lessons Learned

Compared with current traffic simulation packages, Paramics is one of the most cutting edge micro-simulation software programs in the world. In our research, we therefore selected Paramics for our evacuation modeling. However, lots of modeling issues occurred during the modeling process:

1) Current of traffic simulation packages have inadequate modeling capabilities for serious evacuation studies, which includes:

- The packages cannot easily incorporate stochastic modeling and experimentation. Trip demand files and profiles files in our research cannot be generated by the simulator, we have to generate and import these files from other packages.
- The packages cannot model the detailed dynamics within a parking lot. Micro-simulators cannot model such details as the individual parking space; therefore, we have to use a simplified method by aggregating parking spaces into parking zones, ignoring the details inside parking zones.
- The pedestrian modeling tools are in their infancy - One of the modeling issues for the evacuation in shopping areas is to model the interaction between vehicles and pedestrians in the parking lots. We desire to model the panic-stricken situation that

shoppers escape from buildings, drive their cars and leave parking lots to safe zones. In our research, we cannot model the process that pedestrians desperately walking around to find their cars and leave with their cars, since pedestrians are only allowed to travel on predefined route in many micro-simulation packages.

2) Data collection is a serious challenge

Micro-simulators require detailed data in the study region; therefore much effort has to be made in acquiring data. For example, consider our study region. Much time was spent on data collection including: counting parking lot occupancy, road volumes, network structure, road control, parking lot structure, demand patterns, parking lot patterns, evacuation initiation, etc.

3) Model Calibration

This is a serious challenge and a well established problem with the use of microscopic simulation. Not only does it take significant time to calibrate a single evacuation model, but in realistic modeling must calibrate multiple evacuation models during experimentation. At present, trial and error is the major method use for model calibration, which is not an acceptable long term approach.

4) Simulation Result Analysis

Although analysis tools are available in the micro-simulation packages to facilitate simulation results analysis, many packages require post-processing of extensive data sets. In some instances custom programming is necessary to access the desires statistics of evacuation studies. For example, we estimate the evacuation risk as a function of time by using outside statistic packages. These statistics are not readily available within many commercial off the shelf software packages. In our research, the Paramics Analyser of

Paramics was unable to extract our desired data results such as traffic bottleneck locations, because of the necessity of having many zones represent parking locations.

5.2. Future Study

The models developed in this project are only the beginning of the research in these areas, and there are several interesting areas that need study further.

1) Evacuation Strategies

In the model scenario development, we only consider two factors: occupancy rate of a parking lot and background traffic level. In fact, a number of other factors can affect the effectiveness of evacuation such as traffic operations, response rate, evacuation sequence, etc. For example, evacuation time may be much different if a staged evacuation policy is used, rather than simultaneous evacuation.

2) Parking Lot Modeling

As discussed in previous sections, the modeling of parking lots is crucial to the overall evacuation of shopping areas. It not only includes modeling the individual parking spaces as trip generation locations, but also modeling the interaction between pedestrians and vehicles in parking lots at the beginning of an evacuation. This is a deficiency in many simulation packages. The more details we model within parking lots, the more accurate result we will obtain.

3) Pedestrian Modeling

Under evacuation, pedestrians may distribute in the affected regions not only in the parking lots but also on the evacuation routes. The friction between pedestrians and evacuation traffic is inevitable. Therefore the modeling of pedestrians is also an important aspect in evacuation modeling. For example, in order to simulate the movement of pedestrians, we need to determine the distribution of pedestrians at different time of the day, movement mode (e.g. walking or running), and their route choice under an evacuation situation.

References

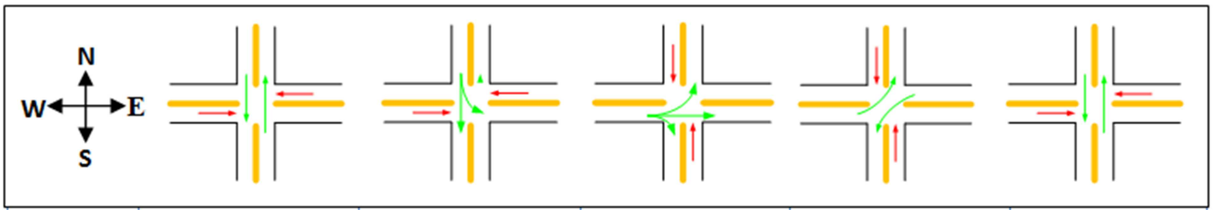
1. Asian Development Bank. 2006. "Indonesia: Tsunami Summary". Available via < http://www.adb.org/Media/Articles/2005/6618_tsunami_impact_Indonesia/default.asp?> [accessed May 3, 2009]
2. Baker, E. J., 2000. "Hurricane evacuation behavioral assumptions for the Florida Keys". *Department of Geography, Florida State University, Tallahassee, FL, U.S.A.*
3. Bartin B., K. Ozbay, O. Yanmaz and N. Rathi. 2005, "Modeling and Simulation of an Unconventional Traffic Circle". *Proceedings of the 8th IEEE on Intelligent Transportation Systems.* pp 384- 389.
4. Benenson, I., K. Martens, and S. Birfir. (2008). "PARKAGENT: An agent-based model of parking in the city". *Computers, Environment and Urban Systems*, vol. 32, no. 6, pp 431-439.
5. Chen, X., and F. B. Zhan. 2008. "Agent-Based Modeling and Simulation of Urban Evacuation: Relative Effectiveness of Simultaneous and Staged Evacuation Strategies". *Journal of the Operational Research Society*, vol. 59, no. 1, pp 25-53.
6. Chen, X., J. W. Meaker, and F. B. Zhan. 2006. "Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys". *Natural Hazards* vol. 38, no. 3, pp 321–338.
7. Choa, F., R. T. Milam, and D. Stanek. 2003. "CORSSIM, PARAMICS AND VISSIM: What the Manuals Never Told You". *Proceeds of 9th TRB Conference on Planning Methods*, Baton Rouge, La.
8. Chu, L., H. X. Liu, J. S. Oh, and W. Recker. 2003. "A Calibration Procedure for Microscopic Traffic Simulation". *Proceedings of 2003 IEEE on Intelligent Transportation Systems*, vol. 2, no. 1, pp1574-1579.
9. Chu, L., H. X. Liu, and W. Recker. 2003. "Development of the capability for enhanced PARAMICS simulation environment". The 82nd Annual Meeting of the Transportation Research Board,Washington, D.C., USA. 1 citation, pp 21
10. Church, R. and R. Sexton. 2002. "Modeling Small Area Evacuation: Can Existing Transportation Infrastructure Impede Public Safety?". *University of California, Santa Barbara*.
11. Cova, T. J., and J. P. Johnson. 2002. "Microsimulation of neighborhood evacuations in the urban-wildland interface". *Environment and Planning A*, vol. 34, pp 2211–2229
12. Cova, T. J., and R. Church. 1997. "Modeling community evacuation vulnerability using GIS". *International Journal of Geographic Information Science* 11:763-784.
13. Fu, H., C. Wilmot. 2004. " A sequential logic dynamic travel demand model for hurricane
Evacuation". *The 83rd Annual Meeting of the Transportation Research Board, Washington, D.C.*.
14. Jha, M., K. Moore, and B. Pashaie. 2004. "Emergency Evacuation Planning with Microscopic Traffic Simulation". *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1886 pp. 40–48.
15. Krogscheepers, C., and K. Kacir, 2001. "Latest trends in micro simulation: an application of the Paramics model". *20th South African Transport Conference, South Africa.* BKS (Pty) Ltd, 222 Durban Road, Bellville, RSA.

16. Liu, Y., G. Chang, Y. Liu, and X. Lai, 2008. "Corridor-Based Emergency Evacuation System for Washington, D.C.: System Development and Case Study". Transportation Research Record: Journal of the Transportation Research Board, vol.2041 pp. 58-67.
17. Miller Consulting Inc.. 2001. "Florida Keys hurricane evacuation report". *Contract No. C7391, Florida Department of Transportation, Miami, Florida*.
18. National Center for Transportation and Industrial Productivity. 2007. "Cape May County Hurricane Evacuation and Elevation Study Extension". *New Jersey Institute of Technology, Newwark, NJ 07102-1983.*
19. Nelson, C. E., M. D. Coovert, A. Kurtz, B. Fritzche, C. Crumley, and A. Powell. 1989. "Models of hurricane evacuation behavior". *Department of Psychology, University of SouthFlorida, Tampa, FL.*
20. Ozbay, K., S. Mudigonda, and B.O. Bartin. 2005. "Development and Calibration of an Integrated Freeway and Toll Plaza Model for New Jersey Turnpike using Paramics Microscopic Simulation Tool". Proceedings of the 8th International IEEE Conference on Intelligent Transportation Systems.
21. Pidd, M., F. N. de Silva, and R.W. Eglese. 1996. "A Simulation Model for Emergency Evacuation". European Journal *of Operational Research, vol. 90, no. 3, pp 413-419.*
22. Radke, J., T. J. Cova, and M. F. Sheridan, A. Troy, L. Mu, and R. Johnson. 2000. "Application Challenges for Geographic Information Science: Implications for Research, Education, and Policy for Emergency Preparedness and Response". *URISA Journal*, vol. 12, no. 2, pp 15-30.
23. Rogers, G. O., and J. H. Sorensen. 1991. "Diffusion of emergency warning: comparing empirical and simulation results". *Risk Analysis Prospects and Opportunitie*, E. C. Zerros, K. E. Knox, L. Abramson, R. Coppock. Plenum Press, New York, pp. 117 – 134
24. Satinnam, T., R. Oshima, A. Fukuda, and P. Klungboonkrong. 2005. "Comprehensive Transportation Policy Development Using Traffic Simulation Technique for Khon Kaen City, Thailand," *Proceedings of the Eastern Asia Society for Transportation Studies*, vol. 5, pp. 2352-2364.
25. Sheffi, Y., H. Mahmassani, and W. B. Powell. 1982. "A transportation network evacuation model". *Transportation Research A*, vol. 16, no. 3, pp 209–218.
26. Sinuany-Stern, Z. and E. Stern. 1993. "Simulating the evacuation of a small city: The effects of traffic factors". *Socio. Econ. Plan. Sci.* vol. 27, no.2, pp 97–108.
27. Sorensen, J.H. 1991. "When shall we leave? Factors affecting the timing of evacuation departures". *International Journal of Mass Emergencies and Disasters*, vol. 19, no. 2, pp. 153-165.
28. Southworth, F.. 1991. "Regional evacuation modeling: a state-of-the-art review". *ORNL/TM- 11740, Oak Ridge National Laboratory, PO Box 2008, Oak Ridge, TN37831*
29. United States Department of Transportation. 2004. "Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software". *FHWA-HRT-04-040, Federal Highway Administration, 400 7th Street, S.W. Washington, D.C. 20590.*
30. Urbanik, T., A. Desrosiers, M. K. Lindell and C. R. Schuller. 1980. "Analysis of techniques for estimating evacuation times for emergency planning zones". Nuclear Regulatory Commission, NuREG/cR-1745. Washington D.C. 20555.

31. Van Der Waerden, P., H. Timmermans, and A. Borgers. 2002. "PAMELA: Parking Analysis Model for Predicting Effects in Local Area". *Transportation Research Record*, no. 1781, pp 10-18.
32. Yue, W., and W. Young. 1996. "Simulation In Selecting the Best Parking Lot Layout". University of South Australia and Monash University.

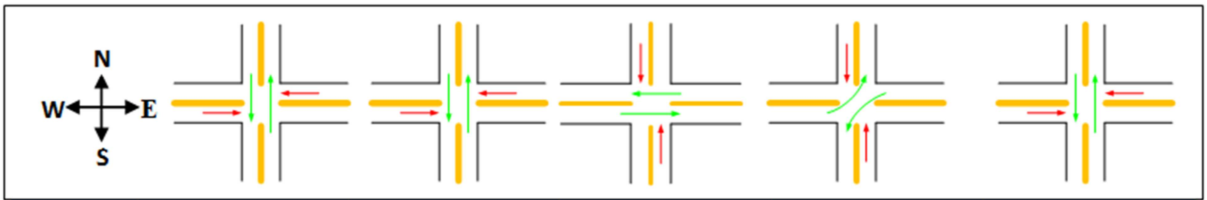
Appendices:

A. Traffic Signals Planning



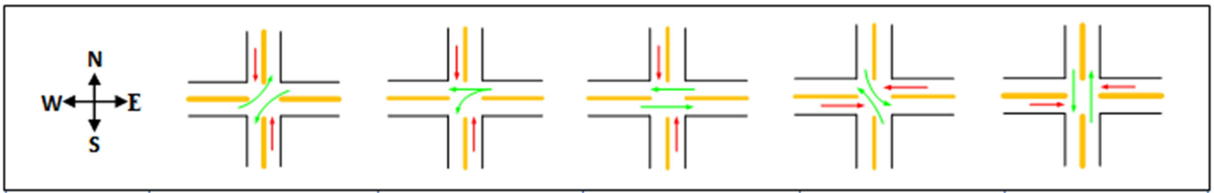
	Phase 1			Phase 2			phase 3			Phase 4			Phase 5		
	R	G	Y	R	G	Y	R	G	Y	R	G	Y	R	G	Y
	3.45	45.5	3.87	2.42	19.54	4.27	1.45	5.41	4.41	8.2	11.52	4.42	0.0	7.41	4.35
	3.37	35.57	4.19	2.54	19.48	4.39		8.62	4.5	4.75	15.31	4.57	0.0	6.12	4.43
	2.92	45.07	4.45		19.39	4.52		8.35	4.53	2.32	9.31	4.53	0.0	6.29	3.45
		40	4.37					5.64	4.4	6.05	15.24	4.55	0.0		
Average	**3**	**42**	**4**	**2**	**19**	**4**	**1**	**7**	**4**	**5**	**13**	**5**	**0**	**7**	**4**

Figure 73. Mall North on N College Ave(1)



	Phase 1			Phase 2			phase 3			Phase 4			Phase 5		
	R	G	Y	R	G	Y	R	G	Y	R	G	Y	R	G	Y
	1.67	44.2	4.32	1.44	16.64	4.38	2.31	9.32	2.26	2.16	5.88	3.92	3.01	5.16	4.31
	1.88	61.28	4.42	1.57	17.75	4.15	2.17	7.42	4.09	1.97	9.93	4.35	2.44	4.28	4.3
	1.91	52.88	4.35	1.49	17.27	4.36	2.29	8.07	1.83	2.07	20.5	4.45	2.18	19.08	5
	2.03	61.71	4.52	1.53	17.55	4.39	2.98	10.08	1.77	2.28	19.55	4.47	2.39	12.45	4.25
	1.77	60.05	4.33	1.51	17.38	4.44				2.11	20.41	4.19	2.51		
	1.83	49.15	4.13	1.49	17.47	4.42				1.87	16.58	4.53			
Average	**2**	**55**	**4**	**2**	**17**	**4**	**2**	**9**	**2**	**2**	**15**	**4**	**3**	**10**	**4**

Figure 74. Mall South on College Ave (2)



	Phase 1			Phase 2			phase 3			Phase 4			Phase 5		
	R	G	Y	R	G	Y	R	G	Y	R	G	Y	R	G	Y
	1.4	6.1	4	1	12.9	3.4	1	18.47	3.66	1	8.4	2.56	0	9.66	3.37
	1.46	5.58	3.37	1	13.23	3.3	1	16.7	4.03	1	7.74	3.3	0	10.5	3.8
	1.4	7.6	3.2	1				16.8	3.3	1	8.6	3.45	0		
	1.5		3.4					17.95	4.05	1	8.15	3.3	0		
								18.1	3.9	1	8.4				
Average	**1**	**6**	**3**	**1**	**13**	**3**	**1**	**18**	**4**	**1**	**8**	**3**	**0**	**10**	**4**

Figure 75. Ejoyce&&North Mall Ave (4)

	Phase 1			Phase 2			phase 3			Phase 4			Phase 5		
	R	G	Y	R	G	Y	R	G	Y	R	G	Y	R	G	Y
	1.4	6.1	4	1	12.9	3.4	1	18.47	3.66	1	8.4	2.56	0	9.66	3.37
	1.46	5.58	3.37	1	13.23	3.3	1	16.7	4.03	1	7.74	3.3	0	10.5	3.8
	1.4	7.6	3.2	1				16.8	3.3	1	8.6	3.45	0		
	1.5		3.4					17.95	4.05	1	8.15	3.3	0		
								18.1	3.9	1	8.4				
Average	**1**	**6**	**3**	**1**	**13**	**3**	**1**	**18**	**4**	**1**	**8**	**3**	**0**	**10**	**4**

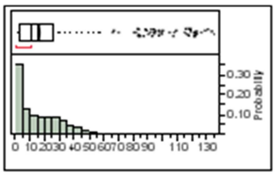
Figure 76. West to the Wal-Mart (5)

B1. Simulation Results from Evacuation Scenarios 1

1) Total evacuation time distribution for different parking lot

➢ Distributions ParkingLotName=Best-Buy

Evacuation Time Distribution



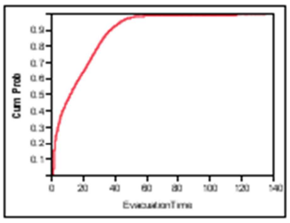
Quantiles

100.0%	maximum	134.73
99.5%		93.90
97.5%		47.56
90.0%		36.32
75.0%	quartile	25.76
50.0%	median	11.28
25.0%	quartile	2.57
10.0%		1.13
2.5%		0.75
0.5%		0.58
0.0%	minimum	0.47

Moments

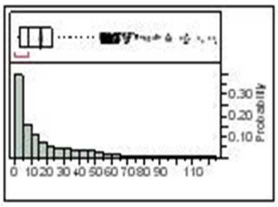
Mean	15.836425
Std Dev	15.860845
Std Err Mean	0.1984778
Upper 95% Mean	16.225508
Lower 95% Mean	15.447342
N	6386

CDF Plot



➢ Distributions ParkingLotName=CCPizza

Evacuation Time Distribution



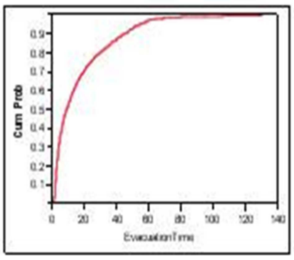
Quantiles

100.0%	maximum	124.35
99.5%		94.78
97.5%		60.18
90.0%		43.92
75.0%	quartile	22.77
50.0%	median	8.28
25.0%	quartile	2.76
10.0%		1.33
2.5%		0.70
0.5%		0.38
0.0%	minimum	0.30

Moments

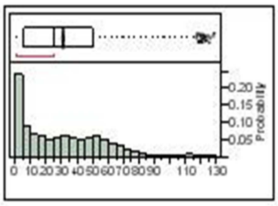
Mean	15.906499
Std Dev	18.20878
Std Err Mean	0.3400097
Upper 95% Mean	16.573187
Lower 95% Mean	15.239811
N	2868

CDF Plot



➢ Distributions ParkingLotName=Loue's-Grill&Bar

Evacuation Time Distribution



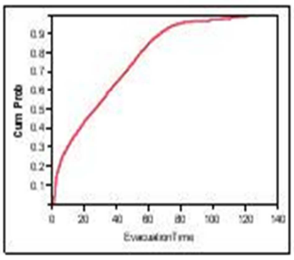
Quantiles

100.0%	maximum	128.25
99.5%		118.72
97.5%		98.05
90.0%		66.06
75.0%	quartile	49.93
50.0%	median	25.95
25.0%	quartile	5.72
10.0%		1.35
2.5%		0.70
0.5%		0.38
0.0%	minimum	0.32

Moments

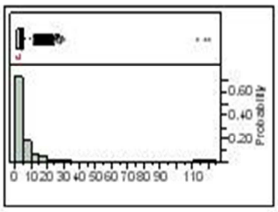
Mean	30.654711
Std Dev	26.881183
Std Err Mean	0.401749
Upper 95% Mean	31.442337
Lower 95% Mean	29.867084
N	4477

CDF Plot



- **Distributions ParkingLotName=LOWE'S**

Evacuation Time Distribution



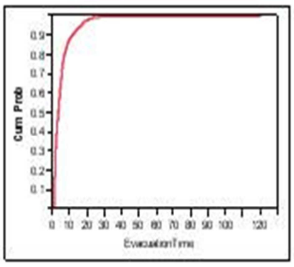
Quantiles

100.0%	maximum	120.27
99.5%		23.94
97.5%		18.67
90.0%		10.93
75.0%	quartile	5.45
50.0%	median	2.85
25.0%	quartile	1.00
10.0%		0.72
2.5%		0.55
0.5%		0.50
0.0%	minimum	0.47

Moments

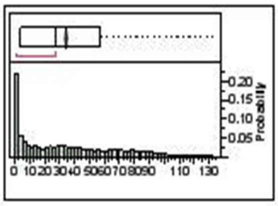
Mean	4.48946
Std Dev	5.8335194
Std Err Mean	0.1002063
Upper 95% Mean	4.6859309
Lower 95% Mean	4.2929892
N	3389

CDF Plot



- **Distributions ParkingLotName=Malco-Cinema**

Evacuation Time Distribution



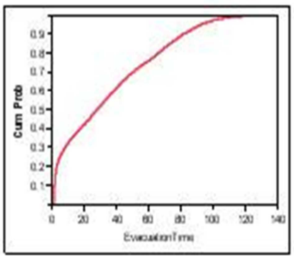
Quantiles

100.0%	maximum	132.27
99.5%		114.72
97.5%		99.78
90.0%		80.83
75.0%	quartile	57.18
50.0%	median	27.33
25.0%	quartile	4.03
10.0%		0.85
2.5%		0.58
0.5%		0.50
0.0%	minimum	0.38

Moments

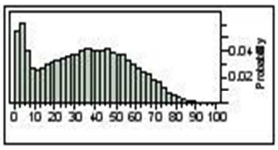
Mean	33.972926
Std Dev	31.050804
Std Err Mean	0.2765896
Upper 95% Mean	34.515084
Lower 95% Mean	33.430769
N	12603

CDF Plot



- **Distributions ParkingLotName=Northwest-Arkansas-Mall**

Evacuation Time Distribution



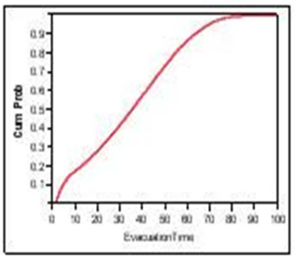
Quantiles

100.0%	maximum	98.550
99.5%		81.480
97.5%		73.630
90.0%		63.120
75.0%	quartile	51.020
50.0%	median	35.070
25.0%	quartile	16.880
10.0%		4.370
2.5%		1.730
0.5%		1.050
0.0%	minimum	0.530

Moments

Mean	34.627171
Std Dev	21.169052
Std Err Mean	0.06677
Upper 95% Mean	34.75804
Lower 95% Mean	34.496303
N	100517

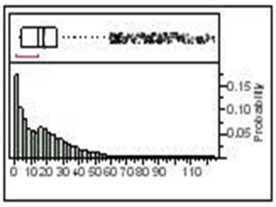
CDF Plot



2) Evacuation time distribution for different parking rows in Wal-Mart

➢ Distributions ParkingRow#=parking row 1

Evacuation Time Distribution



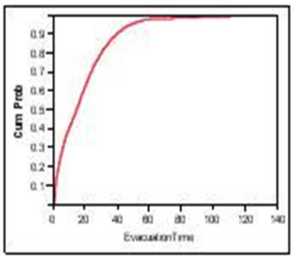
Quantiles

100.0%	maximum	124.52
99.5%		101.65
97.5%		56.18
90.0%		39.30
75.0%	quartile	26.22
50.0%	median	14.37
25.0%	quartile	4.42
10.0%		1.43
2.5%		0.73
0.5%		0.60
0.0%	minimum	0.50

Moments

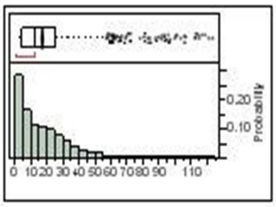
Mean	17.968882
Std Dev	17.102612
Std Err Mean	0.1854275
Upper 95% Mean	18.332365
Lower 95% Mean	17.605399
N	8507

CDF Plot



➢ Distributions ParkingRow#=parking row 2

Evacuation Time Distribution



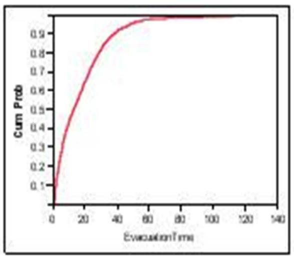
Quantiles

100.0%	maximum	123.42
99.5%		100.37
97.5%		55.77
90.0%		37.23
75.0%	quartile	25.08
50.0%	median	12.48
25.0%	quartile	4.27
10.0%		1.55
2.5%		0.77
0.5%		0.55
0.0%	minimum	0.50

Moments

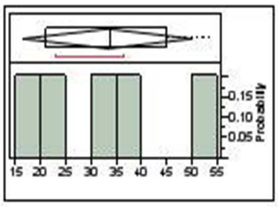
Mean	17.044655
Std Dev	16.802415
Std Err Mean	0.3052967
Upper 95% Mean	17.643265
Lower 95% Mean	16.446045
N	3029

CDF Plot



➢ Distributions ParkingRow#=parking row 3

Evacuation Time Distribution



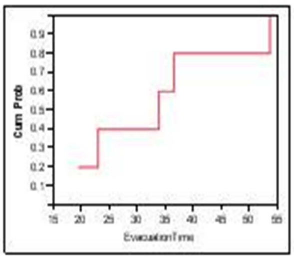
Quantiles

100.0%	maximum	53.680
99.5%		53.680
97.5%		53.680
90.0%		53.680
75.0%	quartile	45.080
50.0%	median	33.780
25.0%	quartile	21.215
10.0%		19.450
2.5%		19.450
0.5%		19.450
0.0%	minimum	19.450

Moments

Mean	33.259614
Std Dev	19.857609
Std Err Mean	0.2738004
Upper 95% Mean	33.796377
Lower 95% Mean	32.722852
N	5260

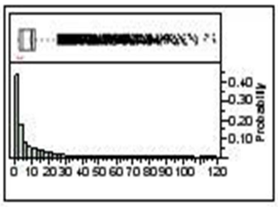
CDF Plot



3) Evacuation time distributions across different destination

➢ Distributions Destination=371

Evacuation Time Distribution



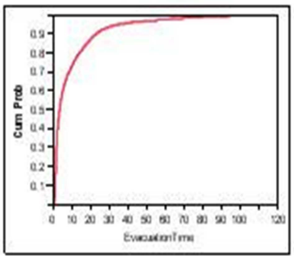
Quantiles

100.0%	maximum	117.68
99.5%		86.91
97.5%		55.71
90.0%		22.57
75.0%	quartile	10.82
50.0%	median	3.27
25.0%	quartile	1.50
10.0%		1.00
2.5%		0.68
0.5%		0.50
0.0%	minimum	0.32

Moments

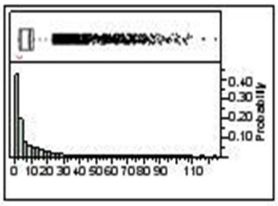
Mean	9.0030834
Std Dev	14.025854
Std Err Mean	0.1228826
Upper 95% Mean	9.2439512
Lower 95% Mean	8.7622155
N	13028

CDF Plot



➢ Distributions Destination=372

Evacuation Time Distribution



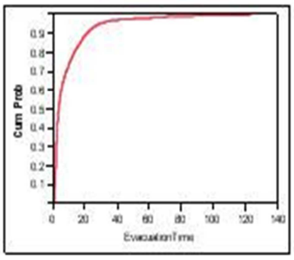
Quantiles

100.0%	maximum	123.07
99.5%		78.79
97.5%		40.91
90.0%		20.55
75.0%	quartile	10.18
50.0%	median	3.25
25.0%	quartile	1.70
10.0%		0.92
2.5%		0.60
0.5%		0.52
0.0%	minimum	0.43

Moments

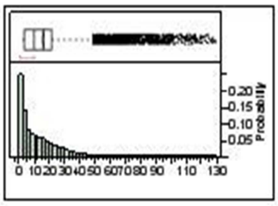
Mean	8.1776963
Std Dev	12.151739
Std Err Mean	0.106292
Upper 95% Mean	8.3860441
Lower 95% Mean	7.9693484
N	13070

CDF Plot



➢ Distributions Destination=373

Evacuation Time Distribution



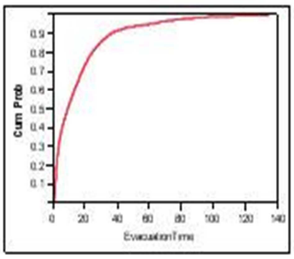
Quantiles

100.0%	maximum	128.20
99.5%		105.46
97.5%		75.17
90.0%		35.71
75.0%	quartile	20.62
50.0%	median	8.85
25.0%	quartile	2.53
10.0%		1.28
2.5%		0.70
0.5%		0.47
0.0%	minimum	0.23

Moments

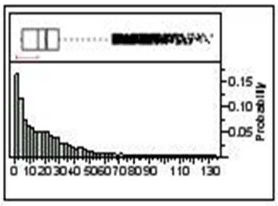
Mean	15.408299
Std Dev	18.98578
Std Err Mean	0.1647701
Upper 95% Mean	15.731272
Lower 95% Mean	15.085326
N	13277

CDF Plot



➢ Distributions Destination=374

Evacuation Time Distribution



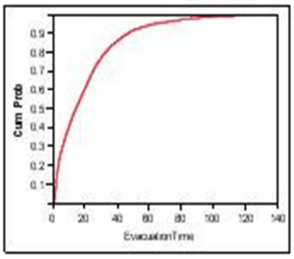
Quantiles

100.0%	maximum	134.73
99.5%		107.12
97.5%		79.56
90.0%		45.92
75.0%	quartile	28.12
50.0%	median	14.03
25.0%	quartile	4.10
10.0%		1.73
2.5%		0.72
0.5%		0.36
0.0%	minimum	0.30

Moments

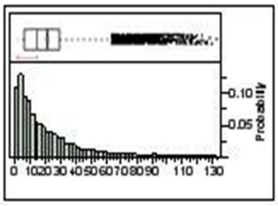
Mean	19.938368
Std Dev	20.584349
Std Err Mean	0.1798944
Upper 95% Mean	20.290987
Lower 95% Mean	19.585749
N	13093

CDF Plot



➢ Distributions Destination=376

Evacuation Time Distribution



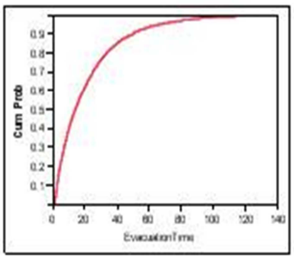
Quantiles

100.0%	maximum	131.02
99.5%		107.27
97.5%		80.78
90.0%		48.93
75.0%	quartile	28.25
50.0%	median	13.45
25.0%	quartile	5.32
10.0%		2.37
2.5%		1.25
0.5%		0.97
0.0%	minimum	0.68

Moments

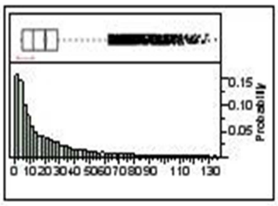
Mean	20.490311
Std Dev	20.877493
Std Err Mean	0.182946
Upper 95% Mean	20.848912
Lower 95% Mean	20.13171
N	13023

CDF Plot



➢ Distributions Destination=377

Evacuation Time Distribution



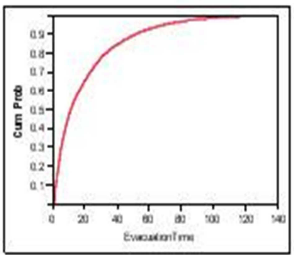
Quantiles

100.0%	maximum	133.10
99.5%		108.90
97.5%		83.42
90.0%		50.74
75.0%	quartile	27.13
50.0%	median	10.83
25.0%	quartile	4.07
10.0%		1.67
2.5%		0.90
0.5%		0.72
0.0%	minimum	0.62

Moments

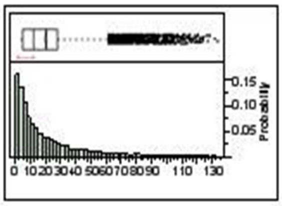
Mean	19.575096
Std Dev	22.097085
Std Err Mean	0.1928645
Upper 95% Mean	19.953139
Lower 95% Mean	19.197054
N	13127

CDF Plot



➢ **Distributions Destination=378**

Evacuation Time Distribution



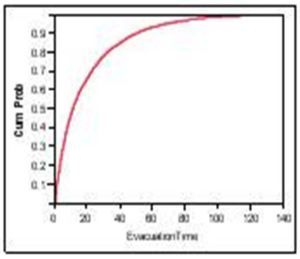
Quantiles

100.0%	maximum	132.27
99.5%		107.48
97.5%		82.16
90.0%		49.26
75.0%	quartile	26.68
50.0%	median	11.20
25.0%	quartile	4.12
10.0%		1.47
2.5%		0.72
0.5%		0.53
0.0%	minimum	0.47

Moments

Mean	19.324209
Std Dev	21.62118
Std Err Mean	0.1881312
Upper 95% Mean	19.692973
Lower 95% Mean	18.955445
N	13208

CDF Plot

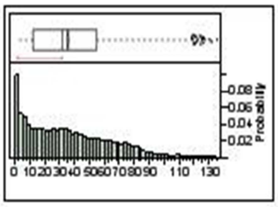


B2. Simulation Results from Evacuation Scenarios 2

1) Total evacuation time distribution for different parking lot

- **Distributions ParkingLotName=Best-Buy**

Evacuation Time Distribution



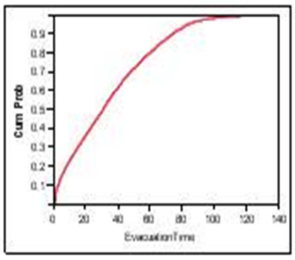
Quantiles

100.0%	maximum	134.35
99.5%		111.12
97.5%		91.93
90.0%		73.66
75.0%	quartile	53.52
50.0%	median	30.48
25.0%	quartile	11.13
10.0%		2.61
2.5%		0.95
0.5%		0.63
0.0%	minimum	0.47

Moments

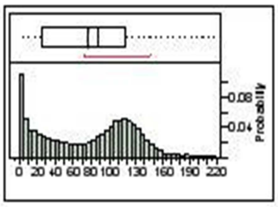
Mean	34.60298
Std Dev	26.778543
Std Err Mean	0.2458714
Upper 95% Mean	35.084928
Lower 95% Mean	34.121032
N	11862

CDF Plot



- **Distributions ParkingLotName=CCPizza**

Evacuation Time Distribution



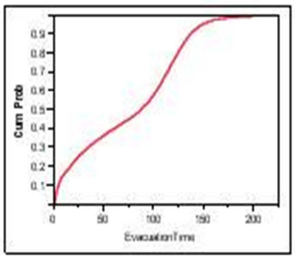
Quantiles

100.0%	maximum	219.30
99.5%		191.20
97.5%		159.78
90.0%		136.55
75.0%	quartile	118.48
50.0%	median	86.92
25.0%	quartile	24.00
10.0%		4.52
2.5%		1.23
0.5%		0.63
0.0%	minimum	0.33

Moments

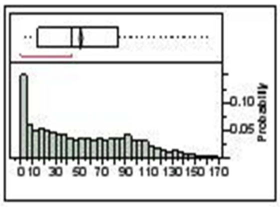
Mean	76.173186
Std Dev	51.05581
Std Err Mean	0.3565979
Upper 95% Mean	76.872146
Lower 95% Mean	75.474225
N	20499

CDF Plot



- **Distributions ParkingLotName=Loue's-Grill&Bar**

Evacuation Time Distribution



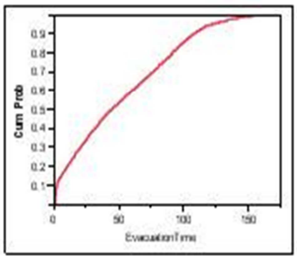
Quantiles

100.0%	maximum	165.07
99.5%		149.54
97.5%		134.35
90.0%		107.23
75.0%	quartile	83.52
50.0%	median	43.75
25.0%	quartile	14.77
10.0%		2.05
2.5%		0.78
0.5%		0.43
0.0%	minimum	0.32

Moments

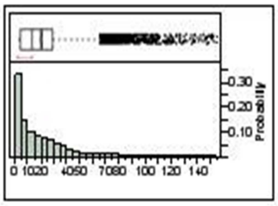
Mean	50.972287
Std Dev	40.076797
Std Err Mean	0.5835258
Upper 95% Mean	52.116271
Lower 95% Mean	49.828304
N	4717

CDF Plot



➢ Distributions ParkingLotName=LOWE'S

Evacuation Time Distribution



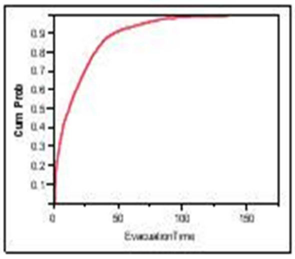
Quantiles

100.0%	maximum	154.22
99.5%		118.50
97.5%		81.72
90.0%		45.92
75.0%	quartile	27.51
50.0%	median	11.77
25.0%	quartile	3.02
10.0%		1.12
2.5%		0.75
0.5%		0.55
0.0%	minimum	0.45

Moments

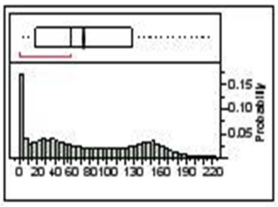
Mean	19.190802
Std Dev	22.197384
Std Err Mean	0.1882419
Upper 95% Mean	19.559781
Lower 95% Mean	18.821822
N	13905

CDF Plot



➢ Distributions ParkingLotName=Malco-Cinema

Evacuation Time Distribution



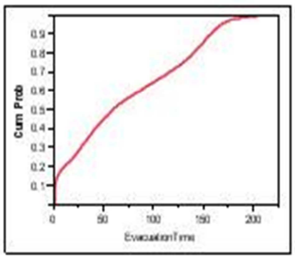
Quantiles

100.0%	maximum	220.40
99.5%		199.71
97.5%		176.61
90.0%		156.67
75.0%	quartile	128.67
50.0%	median	58.73
25.0%	quartile	18.88
10.0%		1.42
2.5%		0.63
0.5%		0.53
0.0%	minimum	0.42

Moments

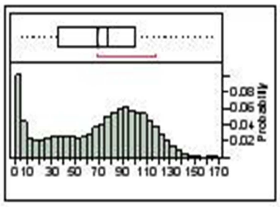
Mean	72.483152
Std Dev	58.719357
Std Err Mean	0.5114546
Upper 95% Mean	73.485677
Lower 95% Mean	71.480628
N	13181

CDF Plot



➢ Distributions ParkingLotName=Northwest-Arkansas-Mall 1

Evacuation Time Distribution



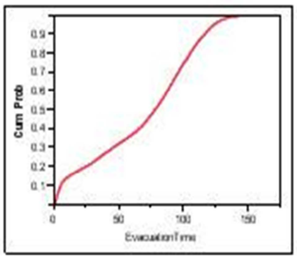
Quantiles

100.0%	maximum	165.23
99.5%		138.94
97.5%		129.32
90.0%		116.02
75.0%	quartile	100.52
50.0%	median	77.92
25.0%	quartile	35.08
10.0%		5.03
2.5%		1.72
0.5%		0.95
0.0%	minimum	0.50

Moments

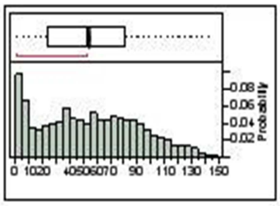
Mean	68.888054
Std Dev	39.606814
Std Err Mean	0.2162596
Upper 95% Mean	69.31193
Lower 95% Mean	68.464177
N	33542

CDF Plot



- **Distributions ParkingLotName=Northwest-Arkansas-Mall 2**

Evacuation Time Distribution



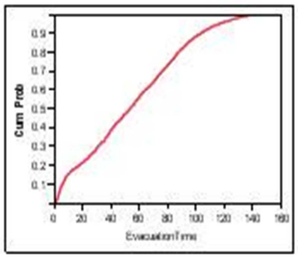
Quantiles

100.0%	maximum	145.55
99.5%		134.82
97.5%		124.90
90.0%		102.48
75.0%	quartile	81.48
50.0%	median	53.13
25.0%	quartile	24.13
10.0%		5.34
2.5%		1.92
0.5%		1.13
0.0%	minimum	0.68

Moments

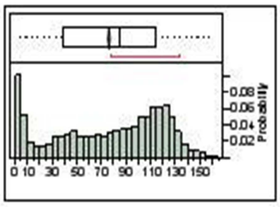
Mean	54.031304
Std Dev	35.564085
Std Err Mean	0.3568023
Upper 95% Mean	54.730709
Lower 95% Mean	53.3319
N	9935

CDF Plot



- **Distributions ParkingLotName=Northwest-Arkansas-Mall 3**

Evacuation Time Distribution



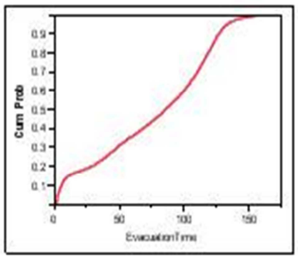
Quantiles

100.0%	maximum	162.78
99.5%		151.47
97.5%		138.97
90.0%		126.58
75.0%	quartile	114.20
50.0%	median	84.93
25.0%	quartile	38.62
10.0%		5.13
2.5%		2.00
0.5%		1.32
0.0%	minimum	0.80

Moments

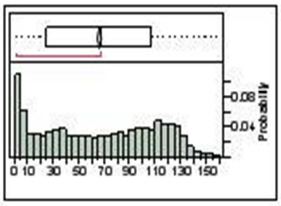
Mean	75.704957
Std Dev	44.276541
Std Err Mean	0.4494675
Upper 95% Mean	76.586007
Lower 95% Mean	74.823907
N	9704

CDF Plot



- **Distributions ParkingLotName=Northwest-Arkansas-Mall 4**

Evacuation Time Distribution



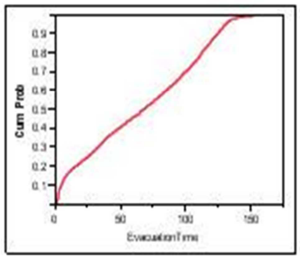
Quantiles

100.0%	maximum	158.48
99.5%		149.25
97.5%		135.41
90.0%		124.13
75.0%	quartile	106.65
50.0%	median	67.28
25.0%	quartile	24.36
10.0%		4.26
2.5%		1.80
0.5%		1.09
0.0%	minimum	0.70

Moments

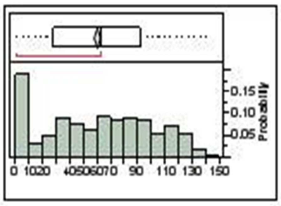
Mean	65.875055
Std Dev	44.367497
Std Err Mean	0.8500831
Upper 95% Mean	67.541928
Lower 95% Mean	64.208182
N	2724

CDF Plot



➢ Distributions ParkingLotName=Northwest-Arkansas-Mall 5

Evacuation Time Distribution



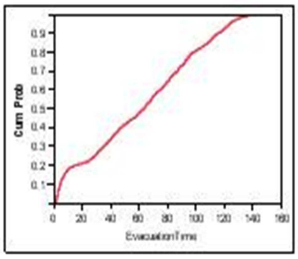
Quantiles

100.0%	maximum	142.17
99.5%		135.46
97.5%		128.10
90.0%		114.49
75.0%	quartile	92.14
50.0%	median	62.78
25.0%	quartile	27.98
10.0%		4.06
2.5%		1.76
0.5%		1.22
0.0%	minimum	1.03

Moments

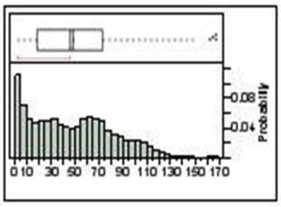
Mean	60.287632
Std Dev	39.436325
Std Err Mean	1.1172167
Upper 95% Mean	62.479468
Lower 95% Mean	58.095797
N	1246

CDF Plot



➢ Distributions ParkingLotName=Northwest-Arkansas-Mall 6

Evacuation Time Distribution



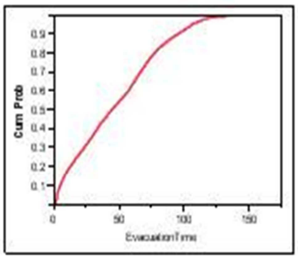
Quantiles

100.0%	maximum	166.13
99.5%		126.92
97.5%		113.68
90.0%		94.88
75.0%	quartile	71.05
50.0%	median	44.42
25.0%	quartile	17.20
10.0%		4.43
2.5%		1.77
0.5%		1.20
0.0%	minimum	0.62

Moments

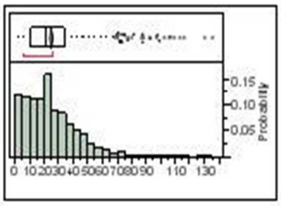
Mean	47.043936
Std Dev	33.17586
Std Err Mean	0.2236818
Upper 95% Mean	47.482369
Lower 95% Mean	46.605504
N	21998

CDF Plot



➢ Distributions ParkingLotName=Northwest-Arkansas-Mall 7

Evacuation Time Distribution



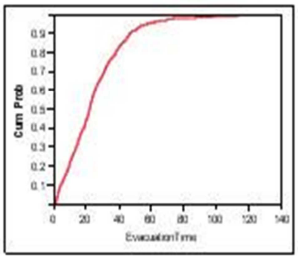
Quantiles

100.0%	maximum	134.93
99.5%		105.62
97.5%		70.17
90.0%		46.49
75.0%	quartile	33.62
50.0%	median	21.77
25.0%	quartile	10.90
10.0%		3.90
2.5%		1.62
0.5%		1.04
0.0%	minimum	0.73

Moments

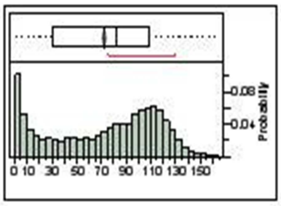
Mean	24.505515
Std Dev	18.322322
Std Err Mean	0.509938
Upper 95% Mean	25.505914
Lower 95% Mean	23.505116
N	1291

CDF Plot



➢ **Distributions ParkingLotName=Northwest-Arkansas-Mall 8**

Evacuation Time Distribution



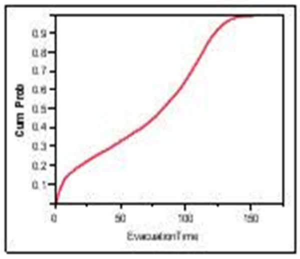
Quantiles

100.0%	maximum	161.98
99.5%		146.92
97.5%		134.49
90.0%		121.98
75.0%	quartile	108.68
50.0%	median	82.02
25.0%	quartile	30.03
10.0%		4.98
2.5%		1.65
0.5%		1.08
0.0%	minimum	0.68

Moments

Mean	71.722172
Std Dev	43.333833
Std Err Mean	0.2851589
Upper 95% Mean	72.281103
Lower 95% Mean	71.163242
N	23093

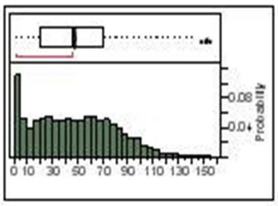
CDF Plot



2) **Evacuation time distribution for different parking rows in Wal-Mart**

➢ **Distributions ParkingRow#=parking row 1**

Evacuation Time Distribution



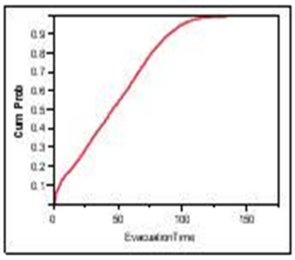
Quantiles

100.0%	maximum	154.72
99.5%		128.21
97.5%		107.55
90.0%		89.16
75.0%	quartile	70.70
50.0%	median	45.60
25.0%	quartile	20.43
10.0%		4.41
2.5%		1.05
0.5%		0.63
0.0%	minimum	0.50

Moments

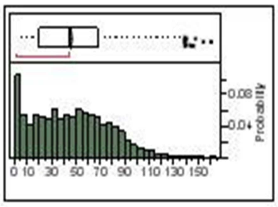
Mean	46.865341
Std Dev	31.27795
Std Err Mean	0.3426602
Upper 95% Mean	47.53704
Lower 95% Mean	46.193642
N	8332

CDF Plot



➢ **Distributions ParkingRow#=parking row 2**

Evacuation Time Distribution



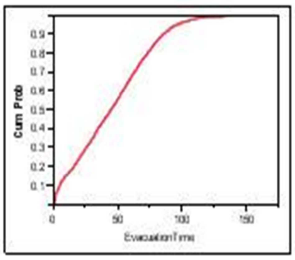
Quantiles

100.0%	maximum	160.17
99.5%		124.25
97.5%		105.50
90.0%		85.32
75.0%	quartile	67.42
50.0%	median	44.60
25.0%	quartile	20.30
10.0%		4.79
2.5%		1.12
0.5%		0.58
0.0%	minimum	0.47

Moments

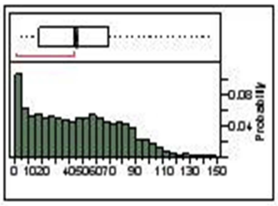
Mean	45.40339
Std Dev	29.891173
Std Err Mean	0.3453378
Upper 95% Mean	46.080349
Lower 95% Mean	44.726431
N	7492

CDF Plot



➢ **Distributions ParkingRow#=parking row 3**

Evacuation Time Distribution



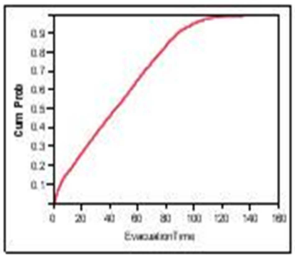
Quantiles

100.0%	maximum	145.57
99.5%		129.15
97.5%		106.53
90.0%		87.58
75.0%	quartile	69.61
50.0%	median	43.86
25.0%	quartile	17.98
10.0%		4.77
2.5%		1.22
0.5%		0.58
0.0%	minimum	0.40

Moments

Mean	45.617972
Std Dev	31.218658
Std Err Mean	0.4241258
Upper 95% Mean	46.449429
Lower 95% Mean	44.786514
N	5418

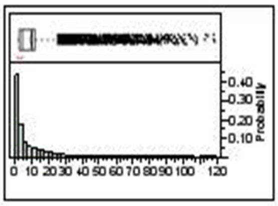
CDF Plot



3) Evacuation time distributions across different destination

➢ **Distributions Destination=371**

Evacuation Time Distribution



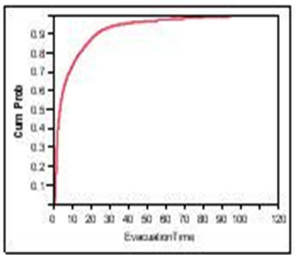
Quantiles

100.0%	maximum	117.68
99.5%		86.91
97.5%		55.71
90.0%		22.57
75.0%	quartile	10.82
50.0%	median	3.27
25.0%	quartile	1.50
10.0%		1.00
2.5%		0.68
0.5%		0.50
0.0%	minimum	0.32

Moments

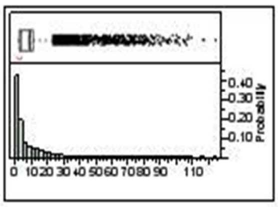
Mean	9.0030834
Std Dev	14.025854
Std Err Mean	0.1228826
Upper 95% Mean	9.2439512
Lower 95% Mean	8.7622155
N	13028

CDF Plot



➢ **Distributions Destination=372**

Evacuation Time Distribution



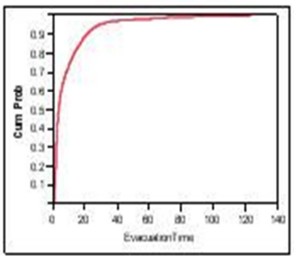
Quantiles

100.0%	maximum	123.07
99.5%		78.79
97.5%		40.91
90.0%		20.55
75.0%	quartile	10.18
50.0%	median	3.25
25.0%	quartile	1.70
10.0%		0.92
2.5%		0.60
0.5%		0.52
0.0%	minimum	0.43

Moments

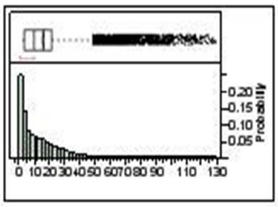
Mean	8.1776963
Std Dev	12.151739
Std Err Mean	0.106292
Upper 95% Mean	8.3860441
Lower 95% Mean	7.9693484
N	13070

CDF Plot



➢ Distributions Destination=373

Evacuation Time Distribution



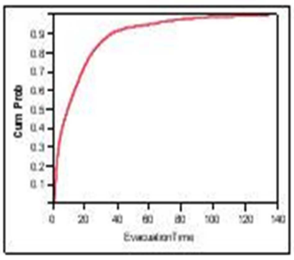
Quantiles

100.0%	maximum	128.20
99.5%		105.46
97.5%		75.17
90.0%		35.71
75.0%	quartile	20.62
50.0%	median	8.85
25.0%	quartile	2.53
10.0%		1.28
2.5%		0.70
0.5%		0.47
0.0%	minimum	0.23

Moments

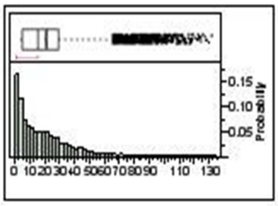
Mean	15.408299
Std Dev	18.98578
Std Err Mean	0.1647701
Upper 95% Mean	15.731272
Lower 95% Mean	15.085326
N	13277

CDF Plot



➢ Distributions Destination=374

Evacuation Time Distribution



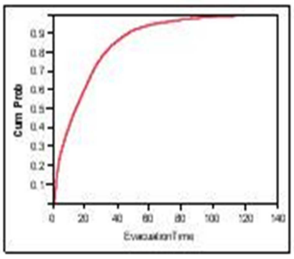
Quantiles

100.0%	maximum	134.73
99.5%		107.12
97.5%		79.56
90.0%		45.92
75.0%	quartile	28.12
50.0%	median	14.03
25.0%	quartile	4.10
10.0%		1.73
2.5%		0.72
0.5%		0.36
0.0%	minimum	0.30

Moments

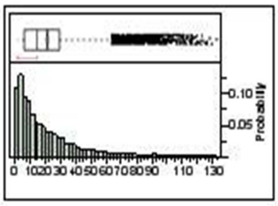
Mean	19.938368
Std Dev	20.584349
Std Err Mean	0.1798944
Upper 95% Mean	20.290987
Lower 95% Mean	19.585749
N	13093

CDF Plot



➢ Distributions Destination=376

Evacuation Time Distribution



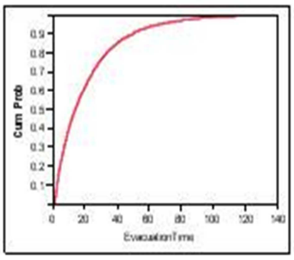
Quantiles

100.0%	maximum	131.02
99.5%		107.27
97.5%		80.78
90.0%		48.93
75.0%	quartile	28.25
50.0%	median	13.45
25.0%	quartile	5.32
10.0%		2.37
2.5%		1.25
0.5%		0.97
0.0%	minimum	0.68

Moments

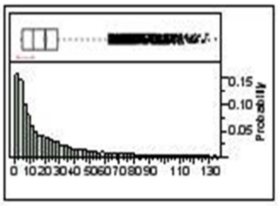
Mean	20.490311
Std Dev	20.877493
Std Err Mean	0.182946
Upper 95% Mean	20.848912
Lower 95% Mean	20.13171
N	13023

CDF Plot



- **Distributions Destination=377**

Evacuation Time Distribution



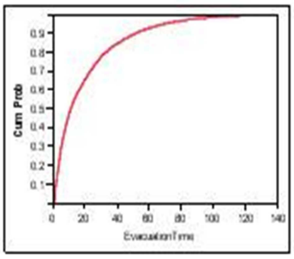
Quantiles

100.0%	maximum	133.10
99.5%		108.90
97.5%		83.42
90.0%		50.74
75.0%	quartile	27.13
50.0%	median	10.83
25.0%	quartile	4.07
10.0%		1.67
2.5%		0.90
0.5%		0.72
0.0%	minimum	0.62

Moments

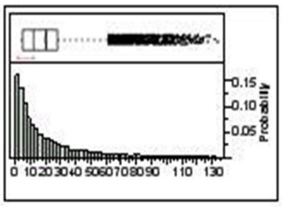
Mean	19.575096
Std Dev	22.097085
Std Err Mean	0.1928645
Upper 95% Mean	19.953139
Lower 95% Mean	19.197054
N	13127

CDF Plot



- **Distributions Destination=378**

Evacuation Time Distribution



Quantiles

100.0%	maximum	132.27
99.5%		107.48
97.5%		82.16
90.0%		49.26
75.0%	quartile	26.68
50.0%	median	11.20
25.0%	quartile	4.12
10.0%		1.47
2.5%		0.72
0.5%		0.53
0.0%	minimum	0.47

Moments

Mean	19.324209
Std Dev	21.62118
Std Err Mean	0.1881312
Upper 95% Mean	19.692973
Lower 95% Mean	18.955445
N	13208

CDF Plot