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Development of trip generation models of hurricane evacuation

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DEVELOPMENT OF TRIP GENERATION MODELS OF HURRICANE EVACUATION

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ABSTRACT

In this study, alternative trip generation models for hurricane evacuation movement were developed using logistic regression and neural networks. The southwest Louisiana post-Andrew survey data were used for model estimation, validation, and comparison. The performance of the alternative models was compared with each other as well as against that of an existing evacuation model, the PBS&J model, developed for the same area. The results showed that the models developed in this study displayed similar performance. It was also found that the models developed in this study performed better than the existing PBS&J model in predicting household evacuation trip generation for southwestern Louisiana. The independent variables found to be significant in explaining household evacuation behavior included housing type, whether the household gets a mandatory evacuation order or not, age of the respondent, distance of the household from the closest body of water, and marital status of the respondent. Comparison of two model specifications involving different numbers of independent variables showed that the more comprehensive specification added very little to the explanatory power of the models and should be abandoned for model parsimony and ease of use.

CHAPTER 1
INTRODUCTION

1.1 General

Hurricanes are one of the most damaging and potentially deadly events that occur frequently in the United States. They bring torrential rains, winds, and flooding and cause millions, or even billions, of dollars in damage. In the United States, on average five hurricanes strike the coastline every three years. Two of these five are major hurricanes which are categorized 3 or higher (defined as having winds above 111 miles per hour on the Saffir-Simpson Scale). In these storms, the losses are not limited to the coastline but often cause damage hundreds of miles inland.

To reduce people's vulnerability to hurricane hazards, several measures can be taken, including imposing appropriate building standards in vulnerable areas, providing sufficient warning so residents can board up their buildings, and managing evacuation from seriously threatened areas. Evacuation is generally aimed at minimizing potential damage by removing people and their property from a high-risk area before disaster strikes and relocating them to a safe area (Perry et al, 1981). The implementation of evacuation is complex because it involves several activities that have to be organized and coordinated to allow the evacuation process to proceed effectively and efficiently in an emergency setting. While not easy, it is imperative that the evacuation process be successful since lives are often at stake. Therefore, a comprehensive, well-conceived evacuation plan must be developed to protect against the possibility that unanticipated problems occur in evacuating traffic. One important component of this planning activity is the ability to estimate how many trips will be generated and when and where trips will be made during an evacuation. To accomplish this goal, the following questions need to be answered:

1) How many people will evacuate and how many vehicle trips will be generated?
2) When will they evacuate?
3) Where will they go?

The above aspects coincide closely with estimation of trip generation and trip distribution (destination selection) in the traditional travel demand estimation process. However, the factors influencing these travel activities are expected to be quite different in evacuation conditions than those encountered in the normal urban environment.

As the review of relevant literature indicates, the majority of research in evacuation modeling in the last twenty years has been focused on the development of models such as MASSVAC, NETVAC, and DYNEV which focus on the estimation of evacuation clearance time. These models all require a given evacuation traffic demand as input. Very few models incorporate travel demand estimation in more than rudimentary form within their procedure. Therefore, to develop more sophisticated models to predict the number of evacuees in hurricanes was determined to be the subject of the research in this study.

1.2 Objectives of Study

The focus of this research study was on travel demand estimation for hurricane evacuations. The primary purpose was to develop trip generation models that estimate the number of hurricane evacuation trips. Different types of trip generation models, including regression and neural network models, were developed and tested.

The specific objectives of this study were:

1) To identify appropriate alternative forms of trip generation models for hurricane evacuation movement.
2) To develop these models using existing evacuation data.
3) To compare the performance of the alternative models of hurricane evacuation trip generation with each other and against existing evacuation models.

CHAPTER 2
LITERATURE REVIEW

Transportation analysis for the evacuation from natural and man-made disasters has evolved substantially since the late 1970s. Some of the earliest work in this area was done for hurricane evacuation (Urbanik, 1978; Corps of Engineers and Southwest Florida Regional Planning Council, 1979). Following this, interest moved toward modeling evacuation from man-made disasters, especially nuclear power plants, after the meltdown accident at Three Mile Island in Pennsylvania on March 8, 1979. However, the 1990s saw a resurgence in interest in hurricane evacuation modeling, and many recent studies have been conducted on this topic.

Lewis (1985) first described a general travel demand forecasting process for hurricane evacuations (see Figure 2.1), which closely parallels the urban travel demand forecasting methodology. He addressed some of the critical problems in evacuation transportation planning, including evacuation travel patterns, estimation of travel demand, calculation of clearance times, and the development of traffic control measures.

Lewis (1985) defined evacuees as all residents living in surge flooded areas in the coastal region and wind-vulnerable residents living in mobile homes or substandard housing in inland areas. Tourists are also generally included among those that will evacuate a threatened area. Evacuation trips are usually considered to originate at the place of residence because most people who are out when the threat arises will return to their residence before evacuating. It was noted that evacuees head for one of the four general destination types: Red Cross/public shelters, hotels/motels, friends/relatives' house, and out of the study area. Lewis suggested that transportation modeling is best performed on a county-by-county basis because evacuation orders are generally issued by a county commission (committee). Each county is divided into evacuation zones, which are smaller geographic areas distinguished by their vulnerability to flooding or other damage during a hurricane. Trip productions by evacuation zone and by destination type are developed for selected hurricane scenarios. To calculate trip attractions, information and data related to the number of hotel/motel units and Red Cross/public shelter capacities are used to estimate the number of vehicles whose destination desires can be satisfied at these facilities. Evacuation vehicle trips are then distributed: productions from each zone are matched with available attractions in all zones to produce trip O-D tables by hurricane scenario by destination type. The loading of the trips onto highway network are then conducted in accordance with assumed behavioral response curves, derived from behavioral research, to determine loading on the network. From assignment of this traffic to the network, clearance times of the network are estimated. This general approach has been applied by Post, Buckley, Schuh & Jernigan, Inc., for several hurricane-vulnerable areas along the southeast coastline of the United States. A study conducted for some Florida coastal counties was used in Lewis' paper to indicate that the most important influences on clearance time are the response rate, evacuation rate, and the time of day at which the hurricane is predicted to strike (Lewis, 1985).

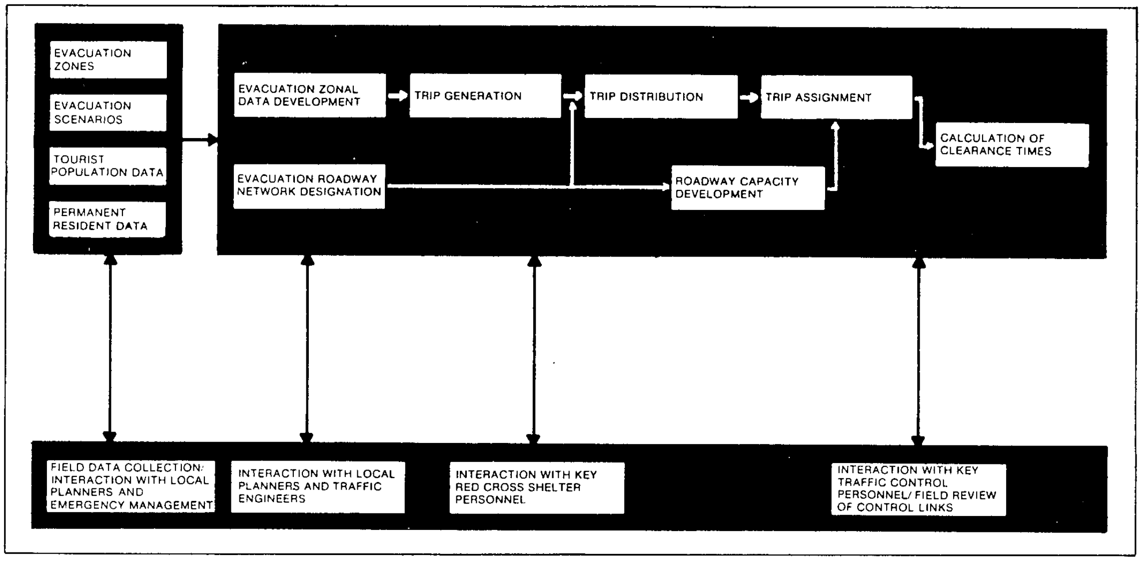

Figure 2.1 Travel demand forecasting process

Another effort at developing a modeling framework is that produced by Barrett et al (2000). They outlined a framework for developing dynamic hurricane evacuation models, including determination and definition of the requirements of the model, development of the model architecture, and general solution methodology. First, with the mission of the model defined to optimize the evacuation system's performance, the functional requirements to the model were determined, which requires the model be capable of storing and analyzing hurricane information, reflecting changes in roadway system, simulating management strategies, and determining changes in travel demand (including dynamic trip generation, trip distribution, and route choice). Specific objectives were defined for both users and system management with respect to destination choice, mode choice, departure time choice, and route choice. Many times users' objectives conflict with system objectives and lead to reduced system performance. Thus, it is important that a capacity of identifying system-optimal conditions be retained in modeling process. The model architecture for both planning and real-time operational purposes was proposed based on the following approach: 1) Under ideal conditions where evacuee behavior is assumed to be completely controlled, minimum total evacuation time can be achieved through optimal utilization of the network; 2) When the actual user-optimized evacuation time achieved based on the destination, mode, departure time, and route choices determined by users exceeds the system optimal evacuation time to a certain extent, emergency management strategies will be developed to change user-optimized choices toward the system optimal evacuation patterns in order to decrease the total evacuation travel time; 3) Update the network and O-D data to reflect the changes which resulted from the management strategies and repeat steps 1) to 3) again until the difference between expected actual evacuation time and system optimal evacuation time is within an acceptable range. The solution process (methodology) of the model was proposed based on a rolling horizon approach to reflect the dynamic nature of the traffic demand and network conditions.

2.1 Evacuation Trip Generation

Strictly speaking, no efforts had been conducted in the area of evacuation trip generation modeling by the early 1990's. The only modeling typically involved was the conversion of the number of evacuating people into number of evacuating vehicles, which were then loaded onto evacuation highway network for traffic analysis (Southworth, 1991, Page 5).

The increase in the development of trip generation models for hurricane evacuation recently is closely related to the availability of data on evacuation and behavior. Most of the post hurricane surveys and behavioral studies were conducted after the late 1980s (Baker 1988, 1990; Irwin et al, 1995; RDS et al, 1999; US Army Corps of Engineers, 2000; PBS&J, 1993, 2000; Prater 2000). The surveys basically collected the following data:

- How many people or what percentage of population evacuated?
- What were the factors affecting people's decision to evacuate?
- Where and what type of destinations did the evacuees head for?
- When did the evacuees leave from their homes?
- How many vehicles were used for the evacuation?
- What are the intentions of the threatened population for future hurricanes?
- Socioeconomic and demographic profiles of the respondents.

After the survey, a behavioral analysis of the data was conducted. The purpose of the behavioral analysis was to analyze the behavior of people in hurricane risk conditions with the intention of being able to provide estimates of public response to a variety of hurricane threat conditions in the future. The output of behavioral analysis usually consists of the following information:

- Number of evacuees/vehicles and evacuation participation rates derived from the sample
- Reasons for evacuating and <u>not</u> evacuating
- People's response to the warning process
- Distribution of evacuation departure times
- Trip end distribution
- Recommended participation rates or number of evacuees for different hurricane scenarios
- Recommended departure time distribution curves for different hurricane scenarios
- Recommended trip end distributions for different hurricane scenarios

- An assessment of possible predictors of whether people evacuate
- Etc.

Behavioral analysis of hurricane evacuation traffic has substituted for the model-building process in the traditional travel demand estimation process. As a result, the 'models' that have been estimated in hurricane evacuation modeling have generally consisted of simple relationships such as means, rates, and distributions rather than the more complex mathematical relationships encountered in traditional travel demand estimation. However, some researchers have developed more sophisticated expressions of travel demand analysis. For example, in a post-storm survey following Hurricane Andrew, Irwin et al (1995) used logistic regression to estimate the probability that an individual would evacuate. Baker has reportedly also used logistic regression to estimate evacuation behavior (Baker, 2001).

In Irwin et al's work, the independent variables entered into the regression model included the respondents' perceptions of whether they were likely to be hurt if they stayed in their homes, the type of dwelling in which respondents were living, prior hurricane experience, the number of individuals living in the household prior to the storm, gender, marital status, education, age, and race. Income was excluded from the formulation because of a large number of missing cases. However, the authors found that the results were unchanged even when income was added to the equation, and they explained that many effects of socioeconomic status were captured by education and race in this particular data set. Based on the estimated model, the authors indicated that perception of risk, type of dwelling, gender, and age significantly affected the probability of evacuating in Andrew. The more strongly individuals felt that they might be hurt if they stayed in their homes, the more likely they were to move. Respondents who were living in either mobile houses or multi-family housing were significantly more likely than others to evacuate. Females were more likely to evacuate than males, and younger individuals were more likely to evacuate than older persons. However, they did not report the goodness of fit of the model. In their model, many variables were not statistically significant (p-value > 0.05), such as hurricane experience, household size, education level, and race. This could make the model numerically unstable. The assumption of linearity of the continuous variables in the model was not investigated. Though the perceived risk of being hurt was the most significant independent variable, it is not a good variable for forecasting travel demand of future hurricanes, because it is practically impossible to forecast. In addition, its influence is affected by other variables, such as the housing type and gender, requiring the inclusion of interactive terms in the model. Therefore, it is suggested that other more attainable variables should be used, such as the intensity of the hurricane, the approaching speed of the hurricane, and the track of hurricane, to substitute for the perception of danger a member of the population may have.

A post-storm socioeconomic impact analysis conducted by Regional Development Service (RDS) and other departments of East Carolina University (1999) revealed a few reasons for both evacuating and <u>not</u> evacuating. Based on a sample of 940 households following Hurricane Bonnie, RDS also used logistic regression to estimate the probability that a household will evacuate in advance of a hurricane. The independent variables included whether the household had been issued a mandatory, voluntary, or no evacuation order, the perceived severity of flood risk, whether the household had a hurricane evacuation plan, whether the household had vehicle(s), whether the respondent was working full-time, whether neighbors evacuated, whether the household had pets, whether the household lived in a mobile home, and the education level of the respondent. The overall regression model was found to be statistically significant at the 99% confidence level (RDS etc, 1999). The analysis of the evacuation decision is presented in Table 2.1, where the dependent variable represents the evacuation decision, which is 1 if evacuating and 0 otherwise.

Table 2.1 Logistic Regression Analysis of Evacuation Decision in Hurricane Bonnie

Variable	Parameter Estimate	Standard Error	t-value	p-value	Odds Ratio
INTERCPT	-6.24	0.91	-6.89	0.0001	.
MANDATOR	1.40	0.26	5.32	0.0001	4.04
VOLUNTAR	0.44	0.24	1.85	0.0638	1.55
FLODRISK	0.50	0.12	4.01	0.0001	1.65
EVACPLAN	0.34	0.19	1.77	0.0760	1.40
VEHICLE	0.95	0.58	1.62	0.1055	2.57
WORKFULL	-0.36	0.19	-1.84	0.0651	0.70
NEIGEVAC	0.89	0.11	7.89	0.0001	2.45
PETS	-0.62	0.19	-3.18	0.0015	0.54
MOBLHOME	1.83	0.24	7.55	0.0001	6.22
EDUC	0.10	0.05	2.16	0.0306	1.11
Model chi-square	317.549	(p=0.0001)			

The *t* values in Table 2.1 indicate that all the factors are significant at the 90% confidence level. The odds ratios in the last column of the table indicate the ratio of the likelihood of evacuating when the independent variable is present to the likelihood of evacuating when the variable is not present. Thus from the results in the table it is shown that those households who were issued a mandatory evacuation order were 4.04 times more likely to evacuate their homes than those who did not get an evacuation order. Those who received a voluntary evacuation order were 1.55 times more likely to evacuate than those who received no order. These results are significant at the 99 percent and 93 percent confidence level, respectively. The probability of an evacuation increases with perceived flood risks (p=0.0001) and if the household has an evacuation plan (p=0.076). Households that have a hurricane evacuation plan are 1.4 times more likely to evacuate than those who do not. Households with running vehicles are 2.57 times more likely to evacuate than those who do not have running vehicles. This result is only significant at the 89 percent confidence level. Households who work fulltime are less likely to evacuate (p=0.065). Households are more likely to evacuate as their neighbors evacuate. For each unit increase in the categorical NEIGEVAC variable (which represent the four extents of the evacuation of the neighbors), households are 2.45 times more likely to evacuate. Households are significantly less likely to evacuate if they have pets (p=0.0015). Households who live in mobile homes are 6.22 times more likely to evacuate than those who do not. Finally, as education of the respondent increases, the probability of an evacuation increases (p=0.03).

This study experienced some of the same problems experienced by Irwin et al (1995). However, a more serious problem with this study was that the numeral associated with some categorical variables was used directly in the model. This is inappropriate because the numbers used to represent categorical variables have, at best, a weak association with the categories they represent.

Behavioral analysis of data from Alabama following Hurricanes Erin and Opal conducted by US Army Corps of Engineers (2000) indicated that 90-95 percent of the high-risk areas, 60-80 percent of moderate risk areas and 20-40 percent of low risk areas evacuated. It was found that in addition to the perceived risk and warning process, there are a variety of human characteristics that have been found to cause differences in evacuation rates, including age, family size, children, pets, race and income. It was also found that, although hurricane threats were different, the response patterns that were observed in earlier hurricanes in the region are consistent with those response patterns observed in Hurricanes Opal and Erin. Thus, fixed evacuation rates for different hurricane scenarios for the region were recommended.

Several studies have used fixed trip rates based on past evacuation surveys and the analyst's judgment (PBS&J, 1992, 2000a, 2000d, and 2001). The rates are used together to produce estimates of travel demand by simple multiplication and addition. Users are not encouraged to change the rates without sufficient new information.

2.2 Evacuation Departure Time

The departure time of evacuees has significant effect on the traffic operational conditions, the severity of traffic congestion, and therefore clearance time on the highway network. A good evacuation model should have the ability to load the evacuation trips onto the highway network in the order in which trips are generated rather than to load all the trips onto the network at the same time as has been done with many evacuation models in the past.

The approaches used to determine evacuation departure time in the past are:

- Generation of behavioral response curves from post evacuation surveys
- Development of mathematical models based on past reported data from surveys

Recently-conducted post-evacuation surveys and behavioral analyses have provided useful information on evacuation departure time. For example, US Army Corps of Engineers (2000) proposed three different response curves, for slow, medium, and rapid responses respectively, based on behavioral analysis of past storms. These curves are illustrated in Figure 2.2. The time point of 0 in the figure is when the evacuation order is issued. The value of 10 percent evacuated at the time the evacuation order is issued reflects the average proportion of the population who elected to evacuate before the order is given (so-called "shadow evacuation") as observed from past behavior. The advantage of this kind of curves lies in its simplicity. The weakness is that it is an average response and is not sensitive to the changing characteristics or the particular circumstances surrounding each hurricane.

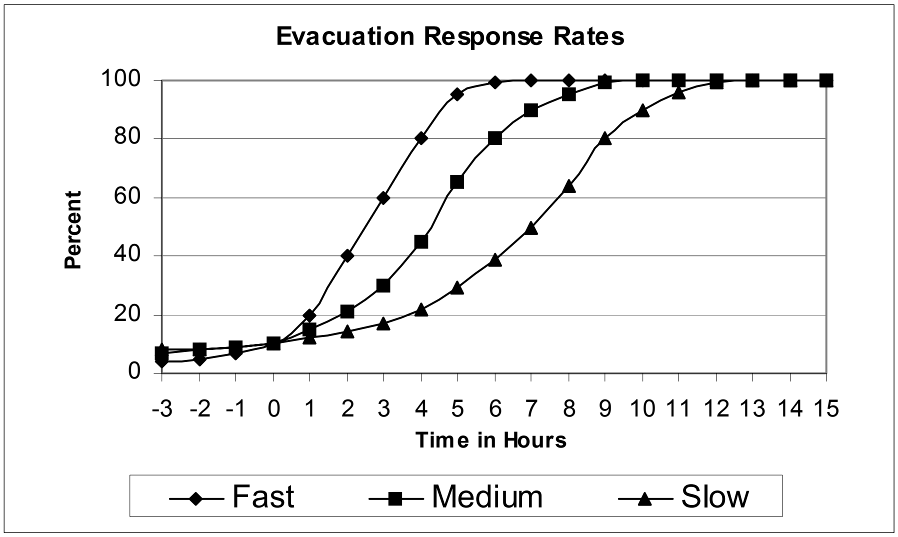

Figure 2.2 Behavioral response curves
(US Army Corps of Engineers, 2000)

The second approach uses the planner's knowledge and judgment, based on the collected data, to produce more general functions for departure time estimation. Tweedie et al (1986) determined mobilization time parameters from information obtained during several meetings with key experts within the Civil Defense Office of Oklahoma. In particular, these experts were questioned to determine the specific amounts of time for which given percentages of the evacuating population could normally be expected to be mobilized. Mobilization time is the time from the issuing of an evacuation order to the time of evacuation departure. The data, shown in Figure 2.3, was then approximated by a Rayleigh probability distribution function given by:

$$F(t) = 1 - \exp(-t^2 / 1800)$$

where $F(t)$ is the percentage of the population mobilized by time t, t is the mobilization time in minutes, and 1800 (minutes) is the maximum time at which all evacuees are assumed to have mobilized.

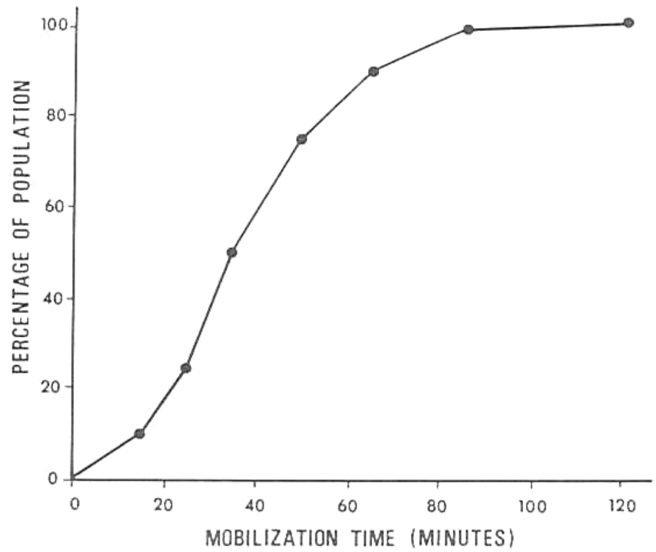

Figure 2.3 Data for mobilization time (in Tweedie 1986)

Radwan et al (1985) and Hobeika et al (1998) used a logistic curve to model the loading time of trips onto the highway network during an evacuation from natural disaster in their MASSVAC model:

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

Where $P(t)$ is the cumulative percentage of the total trips generated at time t. The "α" parameter represents the response of the public to the disaster and alters the slope of the cumulative traffic loading curve. H is the half loading time; the time at which half of the vehicles in the system have been loaded onto the highway network. H defines the midpoint of the loading curve and can be varied by the user according to disaster characteristics.

Southworth and Chin (1987) rearranged the above equation and, by setting $\delta = \exp(\alpha \cdot H)$, they got:

$P(t) = 1/\{1 + \delta[\exp(-\alpha \cdot t)]\}$,

and at $t = 0$,

$\delta = [1 - P(0)] / P(0)$,

which is the ratio of the proportion of vehicles not yet loaded to those already loaded on the network at the time officials issue an evacuation notice or order. This number is important since the percent of evacuees who leave before officials issue an evacuation notice or order, which is the so-called shadow evacuees, are known to some degree from past studies (Lewis, 1985; US Army Corps of Engineers, 2000).

2.3 Evacuation Trip Distribution

The choice of an evacuation destination under threat to life tends to be modeled in one of the following ways (Southworth, 1991):

- Evacuees will choose the closest destination (in terms of distance or travel time) beyond the at-risk area.
- Evacuees will head for pre-specified destinations, according to an established evacuation plan.
- Evacuees will display some degree of dispersion in their selection of destinations, depending on such factors as location of friends and relatives, the characteristics of the hazard, and the traffic conditions on the network at the time they are evacuating.

The first assumption may work effectively in modeling small urban system or rural evacuations when the hazard is approaching rapidly. Some large cities within the US have well-publicized evacuation routes which may favor the second approach above. For example, the Tampa Bay – St. Petersburg conurbation published a newspaper showing residents in different communities how to evacuate in case of hurricanes. A good plan supplemented by effective policing of traffic flow can make this option the best method for evacuation (Southworth, 1991). The third option is more complicated because the selection of destination is influenced by more factors with higher uncertainty. However, this option is closer to the reality, especially for hurricane evacuation.

Almost all hurricane evacuation behavioral studies conducted in the past analyzed the destination type of the evacuated respondents. It has been found that relatives or friends are the most commonly sought destinations during hurricanes: 64% in Southwest Louisiana (Irwin et al, 1995), 68.8% in North Carolina (RDS et al, 1999), and 55-68% in Alabama (Corps of Engineers, 2000). Hotels or motels are the next most popular destination: roughly 13% in Southwest Louisiana, 16.2% in North Carolina, and 17-26% in Alabama. The percentage of the evacuees who went to public shelters was only 12%, 6.4%, and 3-8% respectively in these states. The Corps of Engineers (2000) found that the severity of risk and income are the two most consistent predictors of public shelter demand: evacuees from more hazardous locations tend to use public shelters less than those from less hazardous areas. Poorer people tend to use public shelters more than wealthier people.

The spatial distribution of evacuation trips following past hurricanes have been studied extensively. The implicit assumption was that trip distribution patterns derived from historical data are good indicators of trip distribution patterns that would result from future hurricanes. However, no model of trip distribution appears to have been developed so far to model the process of destination selection in emergency evacuation settings. One exception is the trip distribution model in the Oak Ridge Emergency Management System (OREMS) package, developed by the Oak Ridge National Laboratory (ORNL). The trip distribution submodel of OREMS works as follows. Given the traffic volumes leaving each origin, and a list of its potential destinations for an origin, the algorithm distributes the flow accordingly, i.e., finds out which flows will go where and via which path according to the enroute travel time and the assigned impedance, which will be explained in more detail in section 2.4.5. The model deals with aggregate flows rather than individual vehicles.

2.4 Evacuation Computer Software Packages

Traffic simulation models can be macroscopic, microscopic, or mesoscopic (mixed) depending on the approach used in observing the traffic. The macroscopic models consider the traffic flow as composed of platoons of vehicles, and the relationships between the three critical traffic parameters, speed, flow, and density, are the foundation of these models. On the other hand, the microscopic models are based on factors that govern the movement of individual vehicles in a traffic stream. All microscopic models are based on car-following models. The mesoscopic simulation models apply both the macroscopic traffic flow theory and the car-following theory.

Simulation models, designed to analyze and resolve traffic problems in normal operation conditions, could be applied to model the traffic situation under special conditions such as hurricane evacuation. In the following section, a review of some typical computer models is presented with respect to their application to hurricane evacuation.

2.4.1 NETSIM

The NETSIM network simulation model was developed by KLD Associates, Inc. It is a microscopic, stochastic highway traffic simulation model, which keeps track of every individual vehicle in the system, including an array of characteristics relating to the vehicle type and the behavior of its driver under various traffic situations. It can be used to simulate traffic performance under different control strategies and under heavy traffic demand. The vehicles using the network are processed for each time interval subject to the imposition of traffic control systems. The model also has the capability to model bus operations in detail and calculates fuel consumption and air pollution generated by the traffic in the system. The representation of roadways, intersections, and controls is included in extreme detail. HMM Associates (1980) and Urbanik (1981) first used NETSIM to estimate evacuation time for a nuclear plant area.

Though the NETSIM model is a widely validated procedure and found to perform reasonably well, the application of NETSIM to evacuation analysis has some drawbacks, including that its limited capacity to handle large regional networks and its lack of a dynamic route selection model (every turning movement at every intersection has to be specified *a priori*). Sheffi et al (1982) also pointed out that validations of NETSIM were all conducted in small urban network under normal operating conditions which are probably not indicative of an emergency evacuation in a rural setting. In addition, travel demand models are not incorporated into NETSIM, which means traffic demand has to be submitted to the model as an external input.

2.4.2 NETVAC1 Model

Sheffi, Mahmassani, and Powell (1982) developed the NETVAC1 (NETwork emergency eVACuation) model specifically for nuclear evacuation analysis. NETVAC1 is a fixed-time macro traffic simulation model, using established traffic flow models and relationships to simulate the flow of vehicles through a network and thus to estimate network clearance time for areas surrounding nuclear power plant sites. It is specifically designed to model evacuation traffic patterns including queue formation process, dynamic route selection, and a wide variety of options designed to simulate alternative evacuation scenarios (in terms of weather, intersection controls, lane management strategies, and so forth). It can handle large networks at modest computational costs and has overcome the disadvantages of NETSIM.

The model is sensitive to network topology, intersection design and control, and a wide variety of evacuation management strategies.

The basic features of NETVAC1 include the dynamic route selection, the priority treatment of flow at signalized intersections, and capacity calculations. NETVAC1 requires the following three types of input information (Sheffi, et al 1982):

1) Network Description: connectivity, preference factors, and the physical and operational characteristics of the links;
2) Spatial and temporal traffic loading pattern, specified for any node;
3) Traffic control parameters specifying the control options.

It outputs extensive information on the flows, queues, speeds, and other measures of level of service and flow pattern throughout the evacuation process. This information is given for each link at each specified reporting interval, generating a profile of each link's condition.

The major disadvantages of the model include (Jamei, 1984): 1) the insensitivity to evacuees' behavior; 2) it is structured in a descriptive mode rather than design and planning mode; and 3) it is a deterministic model rather than a probabilistic and dynamic simulation model. In addition, as we can see from the input requirements of NETVAC1, it is not given the capability to estimate the travel demand associated with evacuations, and the spatial and temporal loading pattern has to be input to NETVAC1 as given information.

2.4.3 DYNEV and I-DYNEV Models

The DYNEV (Dynamic Network Evacuation) model was developed by KLD Associates, Inc. It is a macroscopic model for simulating evacuation from sites around a nuclear power plant, which employs the principles of flow continuity and flow dynamics. In the DYNEV model, the road network is represented as a series of links connected at nodes representing the intersection of these segments. The main inputs to the model include: 1) the topology of the network; 2) the geometry of each link; 3) the trips to be loaded onto each link of the network; and 4) the circulation of traffic through the network. The model outputs detailed information, both graphically and in a tabular form, on the operational performance of each link on each route, which includes: 1) speed of evacuating vehicles; 2) density of traffic stream; and 3) the total number of vehicles that used that link. These measures can help identify the bottlenecks on the evacuation route so that appropriate measures can be taken to improve the operations.

I-DYNEV is an evacuation modeling system derived from DYNEV but with improved operational characteristics in certain areas. I-DYNEV and DYNEV were both developed by KLD Associates, Inc. I-DYNEV system consists of three distinctive models: 1) a macroscopic, deterministic traffic simulation model; 2) an equilibrium traffic assignment model; and 3) an intersection approach traffic capacity model (KLD Associates, 1984). The models are applicable to a general system of roads including freeways with access control, rural roads, and urban arterials. The types of traffic control used in the model include traffic signals, stop and yield signs, and no control. It estimates evacuation travel time, moving time, delay time, mean speed, and so on. The IDYNEV model differs from DYNEV in the way it computes the number of vehicles leaving a roadway segment. The improved computational efficiency serves to substantially reduce the computing time and storage.

The number of trips entering and leaving the roadway system is required as input data for both the DYNEV and the I-DYNEV models. A trip generation model or trip distribution model is not incorporated into them.

2.4.4 MASSVAC 3.0 and 4.0

Using macroscopic traffic flow models, Hobeika et al (1985a) developed a mass evacuation computer program, MASSVAC 3.0, which models the evacuation process and utilizes the all-or-nothing traffic assignment or Dial's algorithm to simulate the traffic movements during evacuation. The inputs to the program include the trip production at each origin node, loading rate curve factors, as well as link characteristics such as link length, road capacity, number of lanes, free-flow speed, link type, and coordinates of each origin and destination point. The program loads evacuating vehicles onto the highway network according to loading rate curves, determines their best evacuation routes, estimates network clearance time, and identifies highway bottlenecks. This program includes a trip distribution model. Since people need to be evacuated as quickly as possible from a nuclear disaster area, the model has been developed so that the evacuees choose the shortest routes to get out of the at-risk area first and afterwards seek the proper destination shelter. This is completely different from hurricane evacuation trip distribution, which is usually well planned before the evacuation begins. MASSVAC 3.0 was applied to develop a hurricane transportation evacuation plan for the city of Virginia Beach (Hobeika et al, 1985b). In this study, four scenarios with different hurricane intensity levels and operational strategies were evaluated, and the factors significantly affecting the overall evacuation times under hurricane/flood conditions were found to be the size of the population to be evacuated, the location and number of shelters, the capacity of the evacuation routes, the time available for evacuating from the threatened areas, and the specific traffic operations strategies used for alleviating the congested links.

Due to the shortcoming in Dial's model that the probability of choosing one route is independent of the probability of selecting another available alternative route, MASSVAC 3.0

was recently updated to MASSVAC 4.0, which incorporates the user-equilibrium (UE) assignment algorithm to improve the evacuation performance of the model (Hobeika et al, 1998). The UE assignment is based on the concept that for each O-D pair, the travel time on all used paths are equal and are less than the travel times that would be experienced by vehicles on any unused paths. In addition, MASSVAC 4.0 contains several new traffic management options such as adjustment of link direction, construction of the terminal links, and use of shoulder lanes. However, regardless of MASSVAC 3.0 or 4.0, the inputs for the model require the trip production at each origin node as well as the network attributes.

2.4.5 OREMS

Another model that has been used for hurricane emergencies is the Oak Ridge Evacuation Modeling System (OREMS). This microcomputer-based system was developed by the Center for Transportation Analysis at the Oak Ridge National Laboratory (ORNL) to simulate the traffic conditions over a highway network as evacuation progresses (ORNL 1995). It is an integrated system consisting of three major components: a data input manager, a traffic simulation model, and an output data display manager.

The analytical core of OREMS is a FORTRAN program, ESIM (Evacuation SIMulation), which combines the trip distribution and traffic assignment submodel with a detailed traffic flow simulation submodel. The combined trip distribution and traffic assignment submodel was developed by the researchers at ORNL, and the traffic simulation model was derived primarily from the TRAF simulation system developed by FHWA and therefore has many similarities to that system. The combined algorithm of trip distribution and trip assignment expands the original network by introducing super-destination nodes and adding a set of pseudo-links, which connect the super-destination nodes to the original destination nodes.

Each super-destination node is connected to a subset of destination nodes. These subsets of destination nodes are designed in such a way that the flow needs to be assigned from any origin to a single super-destination node. The algorithm then solves the problem by using the assignment model on the expanded network. The flows on the expanded network are converted into flows on the original network by deleting the super-destination and the pseudo-links.

Given evacuation travel demand, ESIM determines the destinations selected by evacuees and the routes taken to reach the selected destinations through traffic distribution and assignment. It then performs a detailed simulation of vehicular traffic operations on the evacuation network given these projected flows and routes under prevailing roadway and traffic conditions. The model can identify evacuation routes, estimate service rates in the evacuation network by location and by time, identify traffic operational characteristics and bottlenecks, estimate evacuation times across various categories (link, sector, or region specific estimates by time), and provide information on other elements of an evacuation plan. It also allows the analyst to experiment with alternative routes and destinations, various alternative traffic control and management strategies, and different evacuee participation rates (ORNL 1999).

2.4.6 Southeast United States Hurricane Evacuation Travel Demand Forecasting System

A rough form of a trip generation and trip distribution model for hurricane evacuation was developed by Post Buckley, Schuh and Jernigan, Inc., in 2000 and referred to as the Southeast United States Hurricane Evacuation Travel Demand Forecasting System (PBS&J, 2000b). It has subsequently become known as the Evacuation Traffic Information System (ETIS) (Lewis, 2001). The model was developed specifically for the States of Florida, Georgia, Alabama, North Carolina, and South Carolina using data from the post-Floyd hurricane survey in these areas. It is a web- and GIS-based travel demand forecasting model, estimating major traffic congestion areas and traffic flows for a Floyd-type event. The model allows a user to input the category of hurricane, expected participation rate, tourist occupancy, and destination percentages for each county to produce estimates of evacuation information such as expected congestion levels by major highways, tables of expected vehicles crossing state lines by direction, numbers of vehicles generated by each county traveling to specific inland locations, and so on. However, a large number of default values are used for the above information, which were based on out-of-county evacuation traffic data developed in hurricane evacuation studies conducted in the five states of interest. Users are not encouraged to change these values without sufficient justification. These default values serve as the basis of the trip generation module in this system; with them the number of evacuees for each county can be easily estimated by simple multiplication and addition. The default values of destination percentages for each county serve as the basis of trip distribution module.

From the above review, conclusions are drawn as follows:

1) Most of the computer software models developed so far are focused on the assignment of given traffic demand, the simulation of traffic operations on the road network, and the estimation of evacuation clearance time. Trip generation and even trip distribution models for hurricane evacuation are not well developed in these packages.
2) Several techniques have been used to model/estimate trip generation, including the conventional cross-classification method and the logistic regression technique. However, the cross-classification models of PBS&J were achieved using the analyst's judgment on local conditions instead of more sophisticated modeling. The logistic

regression models reviewed also have some serious drawbacks in model specification and the way in which descriptive variables were used.

3) No other techniques were found to model hurricane evacuation trip generation.

Therefore, this relative lack of attention to travel demand modeling of evacuation traffic became one of the factors that prompted the study reported in this thesis.

CHAPTER 3
DATA DESCRIPTION

In this study, trip generation models were developed on the data from a post-Andrew household survey. This survey was conducted in 1995 by Irwin and Hurlbert of the Louisiana Population Data Center at Louisiana State University (LSU) (Irwin and Hurlbert, 1995). The survey collected information on the experiences of respondents living in affected parishes in Southwestern Louisiana when Hurricane Andrew struck in August 1992.

3.1 Hurricane Andrew

Andrew was a hurricane that wrought unprecedented economic devastation along a path through the northwestern Bahamas, the southern Florida peninsula, and south-central Louisiana. Damage in the United States was estimated to be near $25 billion, making Andrew the most expensive natural disaster in U.S. history (Rappaport, 1993). It struck the Gulf coast of Louisiana in the late hours of Tuesday, August 25 and the early hours of Wednesday, August 26. It was one of the worst storms to hit this area in many years. The track of Andrew through the Caribbean, across the Florida peninsula, and across the Gulf and onto land in Louisiana is shown in Figure 3.1. Some attributes of Andrew are shown in Table 3.1.

3.2 The Southwest Louisiana Post-Andrew Survey Data

This survey was conducted by Louisiana Population Data Center in September 1995, with the objective of gathering information about the experiences of respondents who were living in the affected parishes in southwest Louisiana when Hurricane Andrew struck in August 1992. The data were collected in telephone interviews, using computer-assisted telephone interviewing (CATI) technology. In total, 651 households were surveyed, among which 466 households were living in an affected parish when Andrew struck or had evacuated from the parish because of hurricane Andrew. This study was conducted on the data from these 466 households. 194 out of the 466 households evacuated during Andrew.

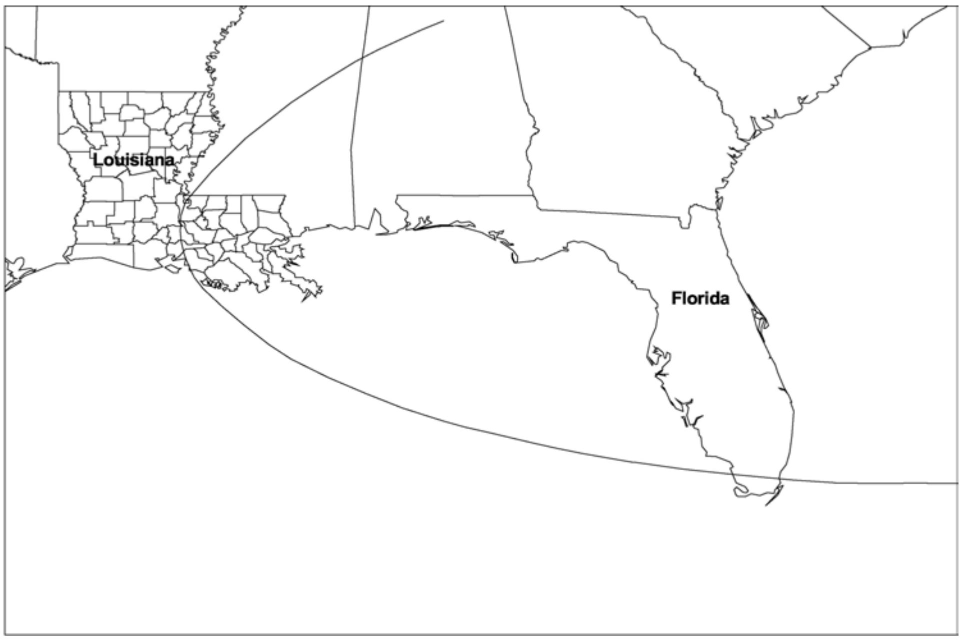

Figure 3.1 Track of Hurricane Andrew, 22-27 August, 1992

Though there are some non-responses on certain data items, an amount of useful information was collected, including how sure the respondent was that his/her home would stand up to Andrew, the respondent's perceived risk of being hurt in the hurricane, the respondent's perceived risk of his possessions being stolen in the hurricane, the housing type, ownership of the residence, previous experience of hurricane evacuation, household size, race, age, education level, marital status, household income of the respondent, whether a mandatory evacuation order was received by the household or not, whether household included children, and so forth. Table 3.2 below shows some information about the database on which the trip generation models were developed in this study.

Table 3.1 Track of Hurricane Andrew, 22-27 August, 1992

Date/Time	Position		Pressure	Wind Speed	Stage	Category
(UTC)	Lat. (°N)	Lon. (°W)	(mb)	(kt)		
22/00:00	25.3	65.9	1000	55	Tropical Storm	
6:00	25.6	67	994	60	" "	
12:00	25.8	68.3	981	70	Hurricane	1
18:00	25.7	69.7	969	80	"	2
23/00:00	25.6	71.1	961	90	"	3
6:00	25.5	72.5	947	105	"	3
12:00	25.4	74.2	933	120	"	4
18:00	25.4	75.8	922	135	"	4
24/00:00	25.4	77.5	930	125	"	4
6:00	25.4	79.3	937	120	"	4
12:00	25.6	81.2	951	110	"	3
18:00	25.8	83.1	947	115	"	3
25/00:00	26.2	85	943	115	"	4
6:00	26.6	86.7	948	115	"	3
12:00	27.2	88.2	946	115	"	4
18:00	27.8	89.6	941	120	"	4
26/00:00	28.5	90.5	937	120	"	4
6:00	29.2	91.3	955	115	"	3
12:00	30.1	91.7	973	80	"	2
18:00	30.9	91.6	991	50	Tropical Storm	
27/00:00	31.5	91.1	995	35	" "	
6:00	32.1	90.5	997	30	Tropical Depression	
12:00	32.8	89.6	998	30	" "	
18:00	33.6	88.4	999	25	" "	

According to the literature (e.g. Baker, 2001), the vulnerability to storm surge of the respondent is a key variable in explaining whether the household evacuates or not. Since this survey did not collect any information about this, data on flood zones in southwest Louisiana were obtained from a GIS database at LSU (http://atlas.lsu.edu) and Dr. John Pine of the Department of Environmental Studies of LSU (Pine, 2002). However, the flood zone data for the parishes of Jefferson Davis and West Baton Rouge could not be obtained and are marked as missing in the data.

Table 3.2 Information for the factors

No.	Factor	No. of Responses	No. of Non-Responses(1)	Total No.
1	Housing type	466	0	466
2	Ownership of the residence	466	0	466
3	Hurricane experience	466	0	466
4	Household size	466	0	466
5	Race	462	4	466
6	Age of the respondent	462	4	466
7	Education level of the respondent	462	4	466
8	Marital status of the respondent	465	1	466
9	Mandatory evacuation order	430	36	466
10	Distance to the nearest body of water	428	3	431
11	Flood zone	453	13	466
12	Children in household	403	63	466
13	Household income	345	121	466

(1) Non-responses include the responses of "Don't know".

3.3 Data Analysis

The evacuation decision was analyzed in terms of the factors in table 3.2. The results are shown in Table 3.3 through Table 3.15.

Table 3.3 shows that 89.7% of the 68 respondents who were living in a mobile home evacuated during Andrew, whereas only 31.2% of those in single houses and 53.8% of those in multi-family buildings did so. Thus, there seems to be a strong association between housing type and evacuation rates. According to Table 3.4, 39.8% of the 362 respondents owning the residence evacuated, while this number increased to 48.1% for those renting a residence. The households with hurricane experience were less likely to evacuate (38.7%) than those without hurricane experience (49.6%), as shown in Table 3.5. Table 3.6 shows that evacuation rates for different household sizes fluctuate with a maximum rate of 56.8% for one-person households and a minimum rate of 30.6% for 3-person households. However, no clear trend in evacuation rates is evident in terms of household size. White people were slightly less likely to evacuate than non-white people (40.9% vs. 46.2%), according to Table 3.7. Age seems to have an association with evacuation rates: approximately 50% of those younger than 40 evacuated while only approximately 30% of those 40 or older did so (Table 3.8). Tables 3.9 and 3.10 show a slight difference in evacuation rates among persons of different education level and marital status, respectively. The association between whether a household received a mandatory evacuation order and the evacuation rate is strong: 62.8% of those who received order evacuated and only 34.4% of those who did not receive an order did so (Table 3.11). Table 3.12 shows that 47.8% of the households living within one mile to the nearest body of water evacuated in Andrew and 35.7% of those farther than one mile did so. Table 3.13 shows that 49.1% of the households who were living in 100-year flood zones and 41% of those living in non-flood zones evacuated. It is also found that the presence of children in the household seemed to affect the evacuation decision: 48.5% of the households having children evacuated, whereas 31.8% of those without children evacuated (Table 3.14).

The analysis on the 345 responses with household income information shows that there seems to be a strong association between household income and the evacuation rate: The evacuation rate decreases with the household income increasing, from 50.8% of those with a household income less than $25,000 per year to 25% of those with a household income greater than $75,000 per year (Table 3.15). However, this phenomenon does not seem logical because richer households should be able to handle the expenses of evacuation more easily than poorer households and therefore more likely to evacuate. Household income might just implicitly indicate a combination of housing conditions of the respondent, such as housing type and location. Hence, richer households with better housing conditions produce a lower evacuation rate.

Table 3.3 Housing type by whether evacuated during Andrew

Housing Type	Evacuation		Total
	Yes	No	
Mobile Home	61 (89.7%)	7 (10.3%)	68 (100%)
Single-Family House	112 (31.2%)	247 (68.8%)	359 (100%)
Multi-Family Building	21 (53.8%)	18 (46.2%)	39 (100%)
Total	194	272	466

Table 3.4 Ownership of the residence by whether evacuated during Andrew

Ownership of Residence	Evacuation		Total
	Yes	No	
Owned	144 (39.8%)	218 (60.2%)	362 (100%)
Rented or other	50 (48.1%)	54 (51.9%)	104 (100%)
Total	194	272	466

Table 3.5 Hurricane experience by whether evacuated during Andrew

Hurricane Experience	Evacuation		Total
	Yes	No	
Yes	132 (38.7%)	209 (61.3%)	341 (100%)
No	62 (49.6%)	63 (50.4%)	125 (100%)
Total	194	272	466

Table 3.6 Household size by whether evacuated during Andrew

Household size	Evacuation		Total
	Yes	No	
1	25 (56.8%)	19 (43.2%)	44 (100%)
2	46 (39.3%)	71 (60.7%)	117 (100%)
3	34 (30.6%)	77 (69.4%)	111 (100%)
4	49 (49.5%)	50 (50.5%)	99 (100%)
5+	40 (42.1%)	55 (57.9%)	95 (100%)
Total	194	272	466

Table 3.7 Race by whether evacuated during Andrew

Race	Evacuation		Total
	Yes	No	
White	157 (40.9%)	227 (59.1%)	384 (100%)
Black and other	36 (46.2%)	42 (53.8%)	78 (100%)
Total	193	269	462

Table 3.8 Age by whether evacuated during Andrew

Age of the respondent	Evacuation		Total
	Yes	No	
<20	18 (47.4%)	20 (52.6%)	38 (100%)
20 – 29	50 (50%)	50 (50%)	100 (100%)
30 – 39	59 (51.8%)	55 (48.2%)	114 (100%)
40 – 49	24 (28.9%)	59 (71.1%)	83 (100%)
50 – 59	26 (36.6%)	45 (63.4%)	71 (100%)
60 +	16 (28.6%)	40 (71.4%)	56 (100%)
Total	193	269	462

Table 3.9 Education level by whether evacuated during Andrew

Education level of the respondent	Evacuation		Total
	Yes	No	
<= 8th Grade	6 (37.5%)	10 (62.5%)	16 (100%)
9th Grade – High school	113 (43%)	150 (57%)	263 (100%)
College	59 (40%)	91 (60%)	150 (100%)
Graduate	13 (40%)	20 (60%)	33 (100%)
Total	191	271	462

Table 3.10 Marital status by whether evacuated during Andrew

Marital Status of the respondent	Evacuation		Total
	Yes	No	
Single	33 (39.8%)	50 (60.2%)	83 (100%)
Married or living with partner	125 (41.9%)	173 (58.1%)	298 (100%)
Separated, divorced, or widowed	36 (42.9%)	48 (57.1%)	84 (100%)
Total	194	271	465

Table 3.11 Mandatory evacuation order by whether evacuated during Andrew

Mandatory Evacuation Order	Evacuation		Total
	Yes	No	
Yes	71 (62.8%)	42 (37.2%)	113 (100%)
No	109 (34.4%)	208 (65.6%)	317 (100%)
Total	180	250	430

Table 3.12 Distance to the nearest body of water by whether evacuated during Andrew

Distance	Evacuation		Total
	Yes	No	
<= 1 mile	96 (47.8%)	105 (52.2%)	201 (100%)
> 1 mile	81 (35.7%)	146 (64.3%)	227 (100%)
Total	177	251	428

Table 3.13 Flood zone by whether evacuated during Andrew

Flood Zone	Evacuation		Total
	Yes	No	
Yes	27 (49.1%)	28 (50.9%)	55 (100%)
No	163 (41%)	235 (59%)	398 (100%)
Total	190	263	453

Table 3.14 Children in household by whether evacuated during Andrew

Children in Household	Evacuation		Total
	Yes	No	
Yes	110 (48.5%)	117 (51.5%)	227 (100%)
No	56 (31.8%)	120 (68.2%)	176 (100%)
Total	166	237	403

Table 3.15 Household income by whether evacuated during Andrew

Household income of the respondent	Evacuation		Total
	Yes	No	
≤ \$25,000	65 (50.8%)	63 (49.2%)	128 (100%)
\$25,000 - \$35,000	31 (47%)	35 (53%)	66 (100%)
\$35,000 - \$50,000	26 (42%)	36 (58%)	62 (100%)
\$50,000 - \$75,000	20 (35.1%)	37 (64.9%)	57 (100%)
> \$75,000	8 (25%)	24 (75%)	32 (100%)
Total	150	195	345

CHAPTER 4
METHODOLOGY OF MODELING TRIP GENERATION

Evacuees can generally be categorized into permanent residents and transients, such as tourists and business people. In trip generation modeling, these two populations should be addressed separately since their evacuation behavior and socioeconomic characteristics are likely to be different. This study focused on the modeling of permanent resident evacuation only since data was not available on transient populations. Since evacuations involve entire households and often include the removal of moveable property such as boats and recreational vehicles, most evacuation trips are generated from the home of each evacuating permanent resident. Thus, trip generation was modeled as originating from home although, depending on the time of day and circumstances, some trips from work to home or school to home may have preceded the trips modeled in this study.

The modeling of evacuation trip generation was done on the southwest Louisiana post-Andrew household survey data described in the previous chapter. The southwest Louisiana post-Andrew survey dataset is at a disaggregate level: each record of the dataset presents the information for each respondent and his/her household, including the household's evacuation decision (evacuating or not), its socioeconomic characteristics, and some subjective judgments of the respondent. The probability of each household to evacuate was estimated using logistic regression and neural network techniques. Due to the relatively small sample size of the data and a relatively large number of independent variables, a cross-classification model was not used in this study.

4.1 Hypotheses for the Models

The hypotheses for the models developed were:

1) A logistic regression model can be developed for evacuation trip generation wherein a set of socioeconomic characteristics describing a household are associated with the household's decision to evacuate. The model can be used to estimate the probability of a household to evacuate during a hurricane.
2) A Back-Propagation Neural Network (BPNN) model can be developed for evacuation trip generation and used to estimate the probability of a household to evacuate during a hurricane.
3) A Probabilistic Neural Network (PNN) model can be developed for evacuation trip generation and used to determine whether or not a household will evacuate during a hurricane.
4) A Learning Vector Quantization neural network model (LVQ) can be developed for evacuation trip generation and used to determine whether or not a household will evacuate during a hurricane.
5) The performance of the above models can be compared with each other and with the performance of existing models used in the region and a conclusion can be drawn as to whether any of the above models have superior performance to existing models.

4.2 Logistic Regression Model

4.2.1 Model Description

Logistic regression is a statistical technique that has been developed specifically for analyzing relationships between dichotomous dependent variables and categorical, interval, or continuous level independent variables. The logistic regression model for evacuation trip generation estimates the probability of a household to evacuate in a hurricane as a function of a certain set of factors, including the socioeconomic characteristics of the household and the hurricane information received by the household.

The logistic regression model for trip generation is given by:

$$y = \frac{e^{(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}}{1 + e^{(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}} \tag{4.1}$$

where:

y = the likelihood that a household evacuates;

x_1, x_2, …, x_n = independent variables; and

β_0, β_1, …, β_n = parameters.

The ratio of likelihood of some event happening to the likelihood that it does not happen, given a set of conditions, is the odds $y/(1-y)$. A logit is the natural logarithm of the odds. Applying the logit transformation $y' = \ln \frac{y}{1-y}$, we obtain $y' = g(\mathbf{x}) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$, where y' or $g(\mathbf{x})$ is called logit or log-odds, which is central to our study of logistic regression. To fit the logistic regression model is actually to fit the log-transformed logistic response function, i.e., $g(\mathbf{x})$, to the observed data. Since neither y nor $g(\mathbf{x})$ is directly measurable, the fitting of this transformed logistic response function is based on maximum likelihood estimation. Once the fitted response function has been obtained, it will be transformed back into the original units to predict the probability on other data.

The dependent variable for equation (4.1) is whether the household evacuated or not, which has a value of 1 or 0, respectively. The set of factors, i.e., independent variables, considered during this exercise consisted of:

- Housing type (mobile home, single-family house, or multi-family building)
- Ownership of the residence (Owned or not)
- Previous experience of being through a hurricane and the damage caused by the most severe hurricane the person experienced (yes and the hurricane destroyed or severely damaged people's houses, yes but the hurricane didn't destroy or severely damage people's house, or no)
- Mandatory evacuation order received (yes or no)
- The distance from the household to the nearest body of water (on the waterfront, not on waterfront but within one block of water, more than one block but less than one mile, or more than one mile)
- Household size
- Whether the household lived in a flood zone when Andrew struck
- Race (white, black, or other)
- Age of the respondent
- Education level of the respondent (Grade 8 and below, high school, college degree, or graduate degree)
- Marital status of the respondent (single and never married, married or living with partner, or separated, widowed, or divorced).

The inclusion of the variables in the model was restricted by the nature of the data available. The southwest Louisiana post-Andrew household survey provided information on the variables discussed above. Household income was not included as an independent variable, because:

1) There are a large number of missing values of household income; and

2) A further investigation revealed that based on the available data a logistic regression model which is much poorer than the one to be presented in Chapter 5 was produced with household income used as an independent variable. In the model, although all the independent variables are significant at $\alpha = 0.05$ level, housing type has to stay out of the model. With housing type entering the model, household income is not significant any more but the model improves substantially.

Some personal characteristics such as age, education level, and marital status of the respondent (individual) were included in the above set of factors and used as independent variables to model the household's decision to evacuate. The reasons why these personal characteristics of the respondent were used to predict the evacuation behavior of a household are as follows:

1) We believe all or some of the characteristics may have significant effects on the household's decision to evacuate.
2) We assumed that the respondent is either the head of the household or an influential member of the household and that their characteristics were therefore influential in the decision-making regarding evacuation in this survey.

Many of the above variables are descriptive and the scale of measurement is nominal (e.g., race and education level). Since it is inappropriate to model a nominal scale variable as if it were an interval scale variable, dummy variables have to be used to represent these variables. The design of dummy variable(s) for each of the above nominal scale variables is shown in Appendix A.

4.2.2 Maximum Likelihood Estimation

A maximum likelihood estimate is a parameter value under which the data actually obtained have the highest probability of being observed (Berry and Lindgren, 1990). The likelihood of the entire observed sample is given as a product of the likelihood of the individual observations, which is written as:

$$L = \prod_{n \in N} \prod_{j \in J} P_n(j)^{\delta_{jn}} \tag{4.2}$$

where,

L = Likelihood of the entire observed sample;

N = All observations;

J = Choice containing all the alternatives;

$P_n(j)$ = Probability of individual n choosing alternative j;

δ_{jn} = 1 if individual n chooses alternative j, and 0 otherwise.

As we can see, the above likelihood function, equation (4.2), is in exponential form. Because the exponential function is monotonic, maximizing the log of the likelihood function is the same as maximizing the likelihood function. The log likelihood function, denoted as L^*, is given by:

$$L^* = \sum_n \sum_j (\delta_{jn} \cdot \ln P_{jn}) \tag{4.3}$$

This non-linear function has been shown to have the property of global concavity (McFadden, 1973) and can be maximized using any of the non-linear optimization algorithms. Since it is more convenient to work with the log likelihood function than with the likelihood function, it is common practice to maximize the function in equation (4.3).

4.2.3 Model Development: Estimation and Validation

The dataset on which the model was developed was first split into two separate datasets, one for model estimation and the other for model validation. The model-estimation dataset has 350 records each containing information for one household. The validation dataset has 60 records containing information of the 60 different households. This split of the dataset was chosen because it is common practice to divide an estimation dataset into an appropriate 85% - 15% split when developing and testing neural network models and it was desirable to use the same dataset on all models developed in this comparative study.

4.2.3.1 Selection of Independent Variables

The traditional approach to statistical model building involves seeking the most parsimonious model that still explains the data. The rationale for minimizing the number of variables in the model is that the resultant model is more likely to be numerically stable and is more easily generalized.

A forward stepwise method was used in this study for variable selection, as it builds models in a sequential fashion and allows for the examination of a collection of models. The forward stepwise method works in the following way: It starts out with a model that contains only the constant. At each step, -2×log likelihood ($-2LL$) values of the model with and without a certain independent variable are calculated. The independent variable in question is selected from among the variables not included in the model up to that point. Variables considered in this fashion are referred to as candidate variables and $-2LL$ is called the likelihood ratio statistics. The significance of the candidate variable is assessed on the computed likelihood ratio statistic and the degree of freedom of the variable. After the significance level of each candidate variables has been assessed, the one with the smallest significance level is selected to enter the model, provided it is less than the chosen cutoff value (0.05 in this case). Since the entry of the new variable may change the significance of other variables, all other variables in the forward stepwise block that have been entered are then examined to see if they meet removal criteria. The variable with the largest significance level for the likelihood-ratio statistic is removed from the model, provided it exceeds the chosen cutoff value (0.10 in this case). If no variables meet the removal criteria, the next eligible variable is entered into the model. If no variables meet the entry criteria, or if a variable is selected for removal which results in a model that has already been considered, variable selection stops. The likelihood ratio test was used for both entry and removal of variables as research has shown it has the best statistical properties.

4.2.3.2 Fitting and Assessing the Model

Once selection of all the variables in the model was completed, the model parameter estimates (the constant and the coefficients of the variables of the logit, y'), the Wald statistics for the coefficients, and the goodness-of-fit of the model (including ρ^2, the Hosmer-Lemeshow test, and the likelihood ratio test) were produced and assessed. Another measure used to assess the performance of the model was the Receiver Operating Characteristics (ROC) curve, which indicates the model's ability to discriminate between those subjects who experience the outcome of interest versus those who do not (Hosmer and Lemeshow, 2000). These tests are described in greater detail below:

1) Hosmer-Lemeshow Test:

The Hosmer-Lemeshow test for binary logistic regression model was proposed by Hosmer and Lemeshow (2000) and is reported as a standard measure in SPSS. The underlying theory of the test is as follows. The values of probabilities estimated by the model are grouped into g

(usually 10) groups based on percentiles of the estimated probabilities. The first group contains the $n_1 = n/10$ subjects having the smallest estimated probabilities, while the last group contains the $n_{10} = n/10$ subjects having the largest estimated probabilities. Then a 2×g table is constructed, where the two rows in the table represent positive and negative predictions by the model respectively. Specifically, the dependent variable y is considered to be equal to one in the first row and equal to zero in the second row. For the $y = 1$ row, estimates of the expected values are obtained by summing the estimated probabilities over all subjects in a group. For the $y = 0$ row, the estimated expected value is obtained by summing the estimated complementary probability over all subjects in the group. The Hosmer-Lemeshow goodness-of-fit statistic, $\hat{C}$, is obtained by calculating the Pearson chi-square statistic from the 2×g table of observed and estimated expected frequencies using the following formula:

$$\hat{C} = \sum_{k=1}^{g} \frac{(o_k - n_k \bar{\pi}_k)^2}{n_k \bar{\pi}_k (1 - \bar{\pi}_k)}$$

Where:

o_k is the number of observed positive responses ($y = 1$) in the k^{th} group;

n_k is the total number of subjects in the k^{th} group; and

$\bar{\pi}_k$ is the average estimated probability in the k^{th} group.

When the number of covariate patterns in the dataset is equal or approximately equal to the number of records in the dataset, distribution of the statistic $\hat{C}$ is well approximated by the chi-square distribution with g-2 degrees of freedom. Corresponding to the statistic $\hat{C}$, a p-value can be found in standard χ^2-distribution tables. When the p-value is lower than 0.05, the null hypothesis that the estimated probabilities for the g groups are the same as the observed probabilities can be rejected; otherwise there are insufficient grounds to reject the hypothesis. The greater the *p*-value is, the better the goodness-of-fit of the model is.

2) Likelihood-ratio Index (ρ^2):

The likelihood ratio index (ρ^2) is commonly used as a goodness-of-fit statistic in maximum likelihood estimation. The likelihood ratio index (ρ^2) is defined as:

$$\rho^2 = \frac{LL(Initial) - LL(\beta)}{LL(Initial)}$$

where,

LL(Initial) is the log likelihood of the model containing the constant only.

$LL(\beta)$ is the log likelihood of the model containing all variables (including the constant).

The likelihood ratio index varies from zero, when through the estimated constant the model reproduces market shares only, to one when the model reproduces observed behavior perfectly. As a general rule:

If $\rho^2 < 0.1$, indicates poor goodness-of-fit

If $0.1 \leq \rho^2 < 0.2$, an acceptable goodness-of-fit

If $0.2 \leq \rho^2 < 0.3$, a good goodness-of-fit

If $\rho^2 \geq 0.3$, an excellent goodness-of-fit

3) Likelihood-ratio Test:

The goodness-of-fit of the whole model can also be evaluated based on the difference, denoted as *G*, between $-2LL$ (Log Likelihood) for the model with only a constant and $-2LL$ for the model with all selected variables included using a Chi-square statistic to test the null hypothesis that the coefficients for all the variables are zero. The distribution of *G* is chi-square with *m* degrees of freedom, where *m* is the number of independent variables in the current model, not including the constant. If the *p*-value is less than 0.05, the null hypothesis can be rejected and we may conclude that the coefficients are significant at a confidence level of 95% or above.

4) Classification Table and Receiver Operating Characteristic (ROC) curve:

The classification table is used to compare the predictions to the observed data by cross-classifying the outcome variable with a dichotomous variable whose values are derived from the estimated probabilities by a logistic model. To obtain the derived dichotomous variable, a cut-point *k* has to be defined and then each estimated probability is compared to *k*. If the estimated probability exceeds *k*, the derived variable is set equal to 1; otherwise it is set equal to 0. The most commonly used value for *k* is 0.5. Hence, a four-cell classification table can be established, and measures of the model performance can be calculated as follows:

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	a	b	a/(a+b)·100%	(a+d)/(a+b+c+d)·100 %
	Not	c	d	d/(c+d)·100%	

A major problem with the classification table is that the values of *a*, *b*, *c*, and *d* are dependent on the defined value of cut-point *k* and hence the percent correct varies widely with *k*. A more complete description of classification accuracy is given by the area under the Receiver Operating Characteristic (ROC) curve. This concept has been widely used in the medical area, which employs the following two parameters: *sensitivity* and *specificity*. In a medical diagnostic perspective, *sensitivity* refers to the proportion of people with disease who have a positive test result, i.e., a/(a+b) in the above classification table, and *specificity* refers to the proportion of people without disease who have negative test result, i.e., d/(c+d) in the classification table. An ROC curve plot shows the false positive rate, i.e., 1-specificity, on the

X-axis and (one minus the false negative rate), i.e., sensitivity, on the Y-axis, which is graphical representation of the trade off between the false negative and false positive rates for an entire range of possible cut-points. The area under ROC curve, which ranges from 0 to 1, represents the probability of correctly distinguishing a true-false pair: The larger this area, the better the model. Therefore, the area under the ROC curve provides a measure of the model's ability to discriminate between those subjects who experience the outcome of interest versus those who do not. As a general rule (Hosmer and Lemeshow, 2000):

If ROC = 0.5, no discrimination

If $0.7 \leq$ ROC < 0.8, acceptable/good discrimination

If $0.8 \leq$ ROC < 0.9, excellent discrimination

If ROC ≥ 0.9, outstanding discrimination

Regression results were also examined closely for incorrect parameter signs and inconsistent parameter estimates, which might indicate problems in the data or in the model. The model developed at the end of this step is referred to as the *preliminary main effects model*.

4.2.3.3 Checking Continuous Variables and Interactions in the Model

For continuous scaled variables their linearity in the logit (log-odds), which was assumed in the variable selection stage, was checked at this stage. After the continuous variable is identified as important, the Box-Tidwell transformation may be employed to test the linearity by adding a term of the form $x\ln(x)$ to the model. If the coefficient for this term is significant, it shows that the logit (log-odds) is not linear in the independent variable, and grouping and use of dummy variables can be considered. Then refit the model with the re-scaled variables. We refer to the model at the end of this step as the *main effects model*.

The next important step is determining whether there is evidence of interaction in the data. In any model an interaction between two variables implies that the effect of one of the variables is not constant over levels of the other, and interaction is incorporated by the inclusion of appropriate higher order terms. The product of the variables in question is the most commonly used form. The need to include interaction terms was assessed using a likelihood ratio test to test the significance of the coefficients of these terms, i.e., inclusion of interactions must contribute to the model. In addition, the interaction term should also make sense from a travel demand modeling perspective. The assessment was done in the same way as for other variables using a stepwise variable selection method with SPSS. We refer to the model at the end of this step as the *final model*.

4.3 Neural Network Modeling

Artificial Neural Networks (ANNs) were tested as a means to model hurricane evacuation travel demand in this study. ANNs are versatile modeling procedures with their highly distributed parallel structures and adaptive learning processes. Among the advantages of ANNs are that they don't suffer the problems often associated with linear regression models, such as multicollinearity, interactions among independent variables, and the assumption of linearity in the model. In addition, neural network models have the advantage of making no assumption of functional form and can approximate any mathematical functions arbitrarily well.

The Feed-Forward Neural Network using Back-Propagation algorithm, which is referred to as BPNN in this study, was first tested for it can approximate any mathematical function, including the logistic function, which makes the comparison between the BPNN model and the logistics regression model more interesting. Also, we can treat an evacuation decision problem as a classification problem, which has two mutually exclusive and complementary classes: the decision to evacuate or not evacuate. Therefore, the Probabilistic Neural Network (PNN) and the Learning Vector Quantizer (LVQ, a modified Kohonen Self-Organizing Network) were tried, as they have strong classification and generalization capabilities and are qualified for solving the problem stated above.

Two model specifications were tried when each neural network model was developed, that is, one including the five variables found significant by the logistic regression technique (i.e., housing type, whether an evacuation order was received, age of the respondent, distance from the household to water, and marital status of the respondent), and the other including all the factors listed in Table 3.2 except the Household Income and Children in Household due to a number of missing values. We will refer to the former as model specification 1 and the latter as model specification 2.

4.3.1 Back-propagation Neural Network (BPNN) Model

4.3.1.1 General

A multi-layer feed-forward back-propagation network using back-propagation (BP) learning algorithm, which is referred to as back-propagation neural network (BPNN) in this study, was employed to model trip generation of hurricane evacuation. The back-propagation neural network has strong classification and generalization capabilities. In the process, an input vector is applied to the network to generate a network output. The difference between this network output and the target output (observed value), that is, the error, is calculated. The network weights for the output layer are adjusted based on the error and the adjustments propagate back in the network to the input layer to minimize the error.

4.3.1.2 Structure of the BP Network

Typically, a BP network has two or more layers. Each layer has a certain number of processing elements called neurons which are usually fully connected with the neurons in successive layers. Figure 4.1 shows a typical three-layer neural network. The neurons in the first layer accept the input data to the network, while the neurons in the last layer contain the output of the network. The layer between the input and output layers is the hidden layer and its neurons together with their interconnections allow input data to be transformed to output data. Each neuron performs three successive activities to complete data processing: summation on input data, activation on the sum, and output of a value. In addition, a bias is usually added to each neuron (excluding those in the input layer) to offset the origin of the activation function, thus producing an effect equivalent to adjusting the threshold of the neuron and often leading to more rapid training.

The generalization properties of the back-propagation neural network are mainly dependent on such factors as the architecture, initial weights of the connections between the neurons, and learning (training) rules.

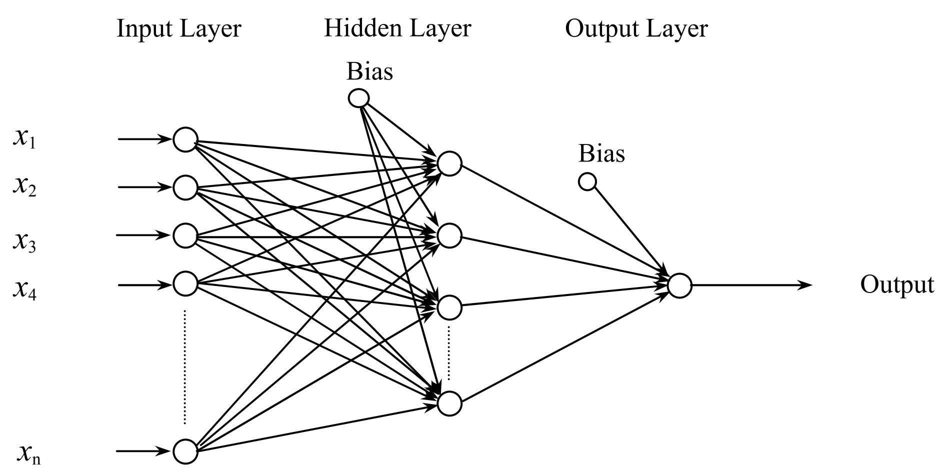

Figure 4.1 Architecture of a typical three-layer BP neural network

4.3.1.3 Model Development: Training and Testing

The Neural Network Toolbox in MATLAB® was used in this study to develop the BPNN model. Three-layer neural networks were used in this study. The network was constructed as follows: The input layer had a number of neurons, each of which corresponds to an explanatory (or independent) variable in the model. The output layer consists of one neuron, which indicates the probability that a household will evacuate. The log sigmoid transfer function was used in the output layer so that the output of the model is within the range of 0 and 1, which is the same as the logistic regression model does. The number of neurons in the hidden layer was determined by trial and error. The transfer function used in the hidden layer neurons was the tangent sigmoid function, because there were many binary inputs in the input dataset; the 0-1 range of the logistic sigmoid function is not optimal for binary inputs and the tangent sigmoid function is preferred in such a case (Stornetta, et al, 1987).

The network was first trained using the training data and then validated on the testing data. The training and testing datasets are the same as used for the logistic regression, PNN, and LVQ models.

The BP neural network was trained with all the records in the training dataset. Each record consists of an input variable pattern and a target output pattern (evacuating or not). Before being presented to the network, input variable data were scaled: all the non-binary input data were scaled into the range of –1 to 1, and the binary variables into the values of 0 and 1. The target outputs were scaled into the values of 0 and 1, 0 representing the household not evacuating and 1 the household evacuating. Training was set to stop after 5,000 iterations or until convergence to a root mean square error (RMSE) of 0.01 is achieved. A number of neural network training rules, such as *Levenberg-Marquardt* training rule, were tried to find the most suitable one.

The records in the testing dataset were used to test the classification and generalization ability of the trained BPNN model. The area under the ROC curve and the Percent Correctly Predicted (PCP) were used to measure the performance of the BPNN model.

4.3.2 Probabilistic Neural Network (PNN) Model

4.3.2.1 General

The probabilistic neural network (PNN) is a neural network solving pattern classification problems by implementing Bayesian Classifiers. The PNN uses training data to develop distribution functions that are in turn used to estimate the likelihood that a given input vector lies within the given categories. Then the input vector is classified into the category with the greatest value of likelihood.

4.3.2.2 Bayes's Classifiers

The Bayes's Law provides a method for categorizing patterns using the following formula

$$P(Y|X) = \frac{P(X|Y) \cdot P(Y)}{P(X)},$$

where Y is interpreted as a possible category into which a pattern might be placed and X is interpreted as the pattern itself. Bayesian decision theory tries to place a pattern in the category that has the greatest value of its decision function based on a set of probability density functions. However, in real-world problems, we rarely have known probabilities and must estimate or approximate such Bayesian probabilities. A probabilistic neural network has this capability: It uses Parzen estimators to obtain the probability density function over the feature space for each category. This allows the computation of the probability that a given vector lies within a given category. Then, combining this information with the relative frequency of each category, the PNN selects the most likely category for a given feature vector.

4.3.2.3 Structure of Probabilistic Neural Networks

The probabilistic neural network consists of four layers as shown in Figure 4.2. The first layer is the input layer and has a number of neurons, each of which corresponds to an explanatory variable. The second layer is called the pattern layer, fully connected to the input layer, with one neuron for each pattern in the training data set. Each of the neurons in the pattern layer performs a weighted sum of its incoming signals from the input layer and then applies a nonlinear activation function to give that neuron's output. The third layer is the summation layer to which each pattern layer neuron transmits its output to a single summation layer neuron. The weights on the connections to the summation layer are fixed at 1.0 so that the summation layer merely adds the outputs from the pattern layer neurons, which generates the networks category choice. There is one summation layer neuron per category: two neurons totally in this case. Each neuron in the output layer receives only two inputs, one from each of two summation units. One weight is fixed at unity, and the other weight has a variable strength equal to

$$w^t = -\left(\frac{h_2}{h_1}\right)\left(\frac{l_2}{l_1}\right)\left(\frac{n_1}{n_2}\right)$$

where h refers to *a priori* probability of patterns being in category 1 or 2, l is loss associated with identifying a pattern as being in one category when it is in reality in the other category, and n is the number of 1 or 2 patterns in the training set. The values for h_1, h_2, n_1, and n_2 are determined by the data pattern present to the network, and l_1 is approximately equal to l_2 if the categorization is wrong in one direction or the other (Tsoukalas and Uhrig, 1997).

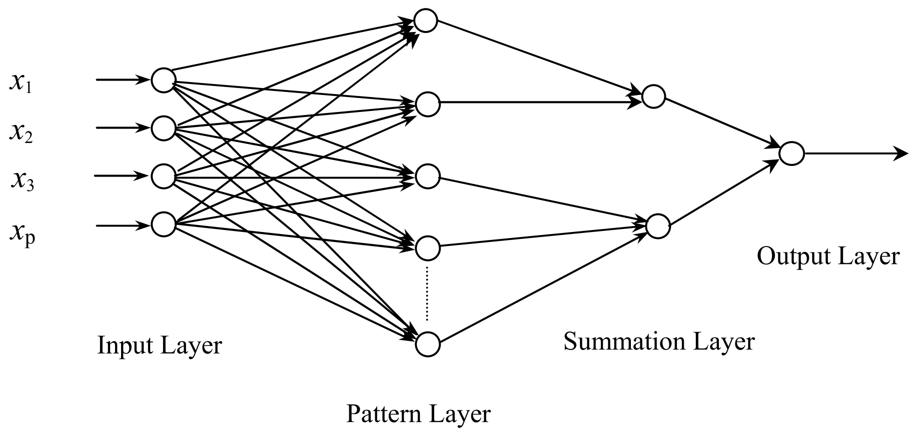

Figure 4.2 Architecture of a PNN

The PNN is trained by setting the weights of one neuron in the pattern layer to the magnitude of each training pattern's elements. That neuron is then connected to the summation unit corresponding to that pattern's category. With a single pass through the training set the network is trained.

The nonlinear activation function used by pattern layer neurons is an exponential function, which is given by:

$$\Phi(I_i) = \exp[(I_i - 1)/\sigma^2]$$

where I is the weighted input to the neuron and the σ is the smoothing parameter that determines how smooth the surface separating categories will be. A reasonable range of values for σ is 0.1 to 10. The shape of the decision surface can be made as complex as necessary using the smoothing parameter. The reason for using the exponential activation function is that it is a simplification of the Parzan estimator of a Bayesian surface, which allows the PNN to approximate Bayesian probabilities in categorizing patterns (Tsoukalas and Uhrig, 1997).

4.3.2.4 Model Development: Training and Testing

The Neural Network Toolbox in MATLAB® was used in this study to develop the PNN models. The determination of the architecture of the PNN model is relatively simple and does not need trial and error in establishing its form: The number of neurons in the input layer is equal to the number of input variables, the number of pattern layer neurons is equal to the number of records in the training set, there is one summation layer neuron per category of the dependent variable, and the output layer always has one neuron. Smoothing parameter is a key factor affecting the surface separating categories and thus the generalization ability of the PNN model. It was determined by trial and error in this study, based on the percent correctly predicted (PCP) by the model on both the training and the testing data.

The network was first trained using the training data and then validated by the testing data. The training and testing datasets are the same as used for the logistic regression model: the training set has 350 records each for one household and the testing set has 60 records. Each record consists of an input variable pattern and a target output pattern (evacuating or not). Before being presented to the PNN, input variable data were scaled: all the non-binary input data were scaled into the range of –1 to 1, and the binary variables into the values of 0 and 1. The target outputs were coded into either 1 or 2, 1 representing the group not evacuating and 2 the group evacuating.

To test the classification ability of the trained PNN model, the testing data were used. As the output falls into either group 1 or group 2, the percentage of exactly matching of estimated and actual decision patterns is used as a criterion to evaluate the model, i.e., compare the predictions to the observed data using the classification table described in section 4.2.3.2.

4.3.3 Learning Vector Quantizer (LVQ) Model

4.3.3.1 General

The Learning Vector Quantizer is a classification network, derived from Kohonen Self-Organizing networks by changing the learning (training) scheme from unsupervised to supervised learning and adding an output layer of neurons to the Kohonen Self-Organization network.

4.3.3.2 Kohonen Self-Organizing Networks (Tsoukalas and Uhrig, 1997)

'Self-Organization' (unsupervised learning) refers to the ability of the network to learn without being given the corresponding output for an input pattern. The Kohonen Self-Organizing network consists of a single layer of neurons (called the Kohonen layer). These neurons are highly (or fully) interconnected (laterally connected) to one another within the Kohonen layer as well as fully connected to the neurons in the input layer.

Kohonen networks utilize lateral inhibition to provide (a) positive or excitatory connections to neurons in the immediate vicinity and (b) negative or inhibitory connections to neurons that are further away. Lateral connections moderate competition between neurons in the Kohonen layer. When an input pattern is presented to the Kohonen layer, each neuron in the layer receives a complete copy of the input pattern modified by the connecting weights and tries to enhance its own output and the output of its immediate neighbors and inhibit the output of the remaining neurons that are further away. The varying responses establish a competition over the intra-layer connections, and the neuron that has the strongest response to the input is determined through the competition. Once the neuron that has the greatest response to the input pattern (i.e., winner) is determined, the network will assign this neuron a +1 value to the output while assigning a zero to all other neurons. The winner neuron is the only neuron that will be allowed to generate an output signal.

Kohonen Learning Rule: Determining the winner is the key to training a Kohonen network. As mentioned above, only the winner and its immediate neighbors modify the weights on their connections, and the remaining neurons experience no training. The training law used is:

$$\Delta w_i = \gamma(x_i - w_i^{old})$$

where γ is the learning constant whose value may vary between 0 and 1, with a typical value of about 0.2, and x_i is the input along the ith connection. This learning law moves the weight vector so that it is more nearly aligned with the input vector. During the training process, the weights tend to cluster around the input vectors. The winning neuron is the one with the weight vector closest to the input vector. Based on this training rule, a Kohonen network can model the probability distribution function of the input vectors spontaneously, with no outside tutor. Many weight vectors cluster in portions of the hypersphere that have relatively many inputs, and few weight vectors cluster in portions of the hypersphere that have relatively few inputs. Kohonen networks perform this statistical modeling, even in cases where no closed-form analytical expression can describe the distribution.

4.3.3.3 Modifications of LVQ

The LVQ network adds an output layer to the Kohonen network, and the number of neurons in the output layer is equal to the number of output pattern categories in the training data set. The Kohonen layer in a LVQ is trained using a modified training procedure as shown below:

$$\Delta w_i = \gamma(x_i - w_i^{old}), \qquad \text{if answer is correct}$$

$$\Delta w_i = -\gamma(x_i - w_i^{old}), \qquad \text{if answer is not correct}$$

That is, if the winning weight vector (the one closest to the input vector) is the correct category for the input pattern, the weight vector is nudged closer to that input pattern. If, however, the winning weight vector is the wrong one, the vector is repelled from the input pattern vector so that another weight vector can win the next time that input pattern is presented to the network. After the training is complete, the activated neurons in the Kohonen layer for input vectors associated with each class are connected directly to the output neuron for that class. Kohonen layer neurons not activated by any input vectors are not connected to the output layer.

4.3.3.4 Model Development: Training and Testing

The Neural Network Toolbox in MATLAB® was used in this study to develop the LVQ models. The architecture of the LVQ network was constructed as follows: The input layer has the same number of neurons as of input variables, and the number of neurons in the output layer is equal to the number of output pattern classes in the training data set (in this case, two). The number of Kohonen layer neurons is arrived at by trial and error, based on the percents correctly predicted (PCPs) by the model on both of the training and the testing datasets.

The network was first trained using the training data and then validated by the testing data. The training and testing datasets are the same as used for the PNN model: the training set has 350 records each for one household and the testing set has 60 records. Each record consists of an input variable pattern and a target output pattern (evacuating or not). Before being presented to the LVQ, input variable data were normalized. This involved dividing each component of the input vector by the vector's length:

$$x_i^{'} = \frac{x_i}{(x_1^2 + x_2^2 + x_3^2 + ... + x_n^2)^{1/2}}$$

Similar to the probabilistic neural network, the target outputs for the LVQ network were coded either 1 or 2, 1 representing the group of the households not evacuating and 2 the group of those evacuating. However, a number of passes of the training set are needed to train the LVQ network.

To test the classification ability of the trained LVQ model, the records in the testing dataset were used. As the output falls into either group 1 or group 2, the percentage of exactly matching of estimated and actual decision patterns is used as a criterion to evaluate the model, i.e., compare the predictions to the observed data using the classification table described in section 4.2.3.2.

CHAPTER 5
ANALYSIS AND RESULTS

In this chapter, the logistic regression and neural network models are developed following the methodology described in the previous chapter. The development of the models is described, the results from the application of the models are analyzed, and the performance of the models evaluated.

5.1 Logistic Regression Model

The developed logit model, $g(\mathbf{x})$, is expressed as:

$$\begin{aligned} g(\mathbf{x}) = {} & 1.796 + 2.315\times\text{ANDHOUS1} - 1.053\times\text{ANDHOUS2} \\ & + 1.444\times\text{MNEVCAND} - 0.04\times\text{AGE} + 0.801\times\text{CURRSWAT} \\ & -1.255\times\text{MARITAL1} - 0.801\times\text{MARITAL2} \end{aligned} \tag{5.1}$$

where:

ANDHOUS1 = 1 if the household lives in a mobile home, and 0 if not

ANDHOUS2 = 1 if the household lives in a single family house, and 0 if not

MNEVCAND = 1 if the household gets a mandatory evacuation order, and 0 if not

AGE = the age of the respondent

CURRSWAT = 1 if the household lives within one mile to the body of water, and 0 if not

MARITAL1 = 1 if the respondent is single and never married, and 0 if not

MARITAL2 = 1 if the respondent is married or living with partner, and 0 if not

Therefore, the probability of a household evacuating can be expressed as

$$y = \frac{e^{g(\mathbf{x})}}{1 + e^{g(\mathbf{x})}} \tag{5.2}$$

The process of the development of this model is explained step by step as follows.

Fitting the model:

The results of applying stepwise variable selection using the Likelihood Ratio test at each step are presented in Table 5.1 in terms of *p*-value. The definition of the variables is shown in Appendix A. Different coding schemes for some variables, such as marital status, distance to water, and hurricane experience, were tried, taking into account that they might have an effect on the significance of the variable in the model. Indeed, the existence of the effect was proved in the trials, which can be seen from Table 5.1 where, for example, the distance from the household to the closest body of water was found to be significant when grouped into two classes: 1) being within one mile, and 2) more than one mile, but not significant when grouped into four classes: 1) being on the waterfront, 2) being not on waterfront but within one block of water, 3) being more than one block of water but within one mile, and 4) being more than one mile. The similar effect was also found on marital status of the respondent.

The variable that enters the model at each step is indicated by underlining its *p*-value at that step. Due to the entrance of the new variable, the *p*-value(s) of the variable(s) that entered the model before is (are) checked for the removal purpose, which is (are) shown in the cell(s) crossed by the corresponding variable row and step column. Based on the pre-set removal criterion (p-value > 0.1), no variables were removed from the model at any step. Consequently, five variables, i.e., housing type, whether the household gets mandatory evacuation order, age of the respondent, distance from the household to the closest body of water, and marital status of the respondent, are finally selected to the model whose coefficients are all significant at α=0.05 level. The results are shown in Table 5.2.

Table 5.1 Results of Forward Stepwise Variable Selection for the Development of Logistic Regression Model, Presented at Each Step in Terms of *p*-Value

Variable	df	Step					
		0	1	2	3	4	5
ANDHOUS1							
ANDHOUS2	2	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
MNEVCAND	1	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
AGE	1	0.003	0.033	0.003	0.003	0.002	0.001
CURRSWAT	1	0.028	<0.001	0.012	0.009	0.009	0.004
MARITAL1							
MARITAL2	2	0.891	0.729	0.849	0.108	0.05	0.05
OWNRES	1	0.088	0.185	0.384	0.822	0.751	0.835
PHURRSEV1							
PHURRSEV2	2	0.254	0.826	0.69	0.856	0.83	0.852
PHURRSEV1_Only	1	0.119	0.536	0.41	0.661	0.794	0.846
HUREXPAN	1	0.14	0.723	0.432	0.995	0.787	0.766
DISTWAT1							
DISTWAT2							
DISTWAT3	3	0.173	0.004	0.063	0.049		
RACE1_Only	1	0.067	0.293	0.835	0.828	0.908	0.893
RACE2_Only	1	0.235	0.405	0.995	0.67	0.727	0.907
HHSIZE	1	0.682	0.388	0.862	0.651	0.584	0.759
MARITAL2_Only	1	0.669	0.655	0.6	0.695	0.577	
EDUCAT1							
EDUCAT2							
EDUCAT3	3	0.905	0.90	0.423	0.52	0.57	0.673
FLOODZON	1	0.446*	0.701*	0.779*	0.822*	0.782*	0.873*

*: The *p*-values of FLOODZON are calculated on a sample of 340 households instead of 350, due to missing values.

Table 5.2 Main Effects Model

	β	**S.E.**	**Wald**	**d.f.**	**Significance**
Constant	1.796	0.770	5.444	1	0.020
ANDHOUS1	2.315	0.656	12.438	1	0.000
ANDHOUS2	-1.053	0.464	5.156	1	0.023
MNEVCAND	1.444	0.306	22.251	1	0.000
AGE	-0.040	0.011	13.643	1	0.000
CURRSWAT	0.801	0.280	8.183	1	0.004
MARITAL1	-1.255	0.537	5.472	1	0.019
MARITAL2	-0.801	0.386	4.293	1	0.038

Log likelihood (β) = -178.88
Log likelihood (Initial) = -238.102

Therefore, the preliminary main effects model is expressed as:

$$\begin{aligned} g(\mathbf{x}) = 1.796 &+ 2.315\times\text{ANDHOUS1} - 1.053\times\text{ANDHOUS2} \\ &+ 1.444\times\text{MNEVCAND} - 0.04\times\text{AGE} + 0.801\times\text{CURRSWAT} \\ &-1.255\times\text{MARITAL1} - 0.801\times\text{MARITAL2} \end{aligned} \tag{5.3}$$

Assessing the model:

The logistic regression model developed above has a $\rho^2 = \frac{(-238.102)-(-178.88)}{(-238.102)} = 0.25$, indicating that the model fits the data well.

The value of the likelihood-ratio statistic is G = -2[(-238.102) – (-178.88)] = 118.444. The p-value for the test is $P[\chi^2(7)>118.444] < 0.001$ based on 7 degrees of freedom, which is significant at the α=0.001 level. Therefore, we reject the null hypothesis with 99.9% confidence and conclude that the coefficients for all the variables are different from zero.

The value of the Hosmer-Lemeshow goodness-of-fit statistic is $\hat{C} =$ 7.488 and the corresponding p-value computed from the chi-square distribution with 8 degrees of freedom is 0.485 > 0.05. This indicates that the null hypothesis that the estimated probabilities for the 10 groups are the same as the observed probabilities cannot be rejected and that, therefore, by implication the model fits the data well.

The percent correctly predicted by a logistic regression model changes with the value of cut-point k, and therefore the selection of k is critical. In this study, the criterion for the selection of k is to maximize the average of sensitivity and specificity, as sensitivity and specificity are considered of similar importance. It was observed that the average of the sensitivity and specificity on the data for model estimation reached the maximum, 74.02%, when k = 0.36. The percent correctly predicted by the logistic regression model on the model estimation data and the testing data using a k value of 0.36 are shown in Table 5.3 and Table

5.4, respectively. From the tables, it can be observed that, on the data used for model estimation, 74.15% of the households who evacuated and 73.89% of the households who did not evacuate were correctly predicted by the model, which produces an overall percent correctly predicted of 74%. On the testing data, 63.64% of the households who evacuated and 68.42% of the households who did not evacuate were correctly predicted by the model, and the overall percent correctly predicted is 66.67%.

Table 5.3 Percent correctly predicted by logistic regression model on the estimation data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted	Average of Sensitivity and Specificity
		Evacuated	Not			
Observed	Evacuated	109	38	74.15% (109/147)	74% (259/350)	74.02%
	Not	53	150	73.89% (150/203)		

Table 5.4 Percent correctly predicted by logistic regression model on the testing data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted	Average of Sensitivity and Specificity
		Evacuated	Not			
Observed	Evacuated	14	8	63.64% (14/22)	66.67% (40/60)	66.03%
	Not	12	26	68.42% (26/38)		

A plot of sensitivity versus (1- specificity), calculated on the model estimation data, over the full range of possible cut-points is shown in Figure 5.1. The resulting curve is called the Receiver Operating Characteristic (ROC) Curve. The area under the ROC Curve in Figure

5.1 is 0.81, indicating the model has excellent discrimination ability. The ROC curve estimated on the testing data is plotted in Figure 5.2 and the area under the curve is 0.68, which is nearly acceptable. The roughness of this ROC curve is also due to the small sample size of the testing data set.

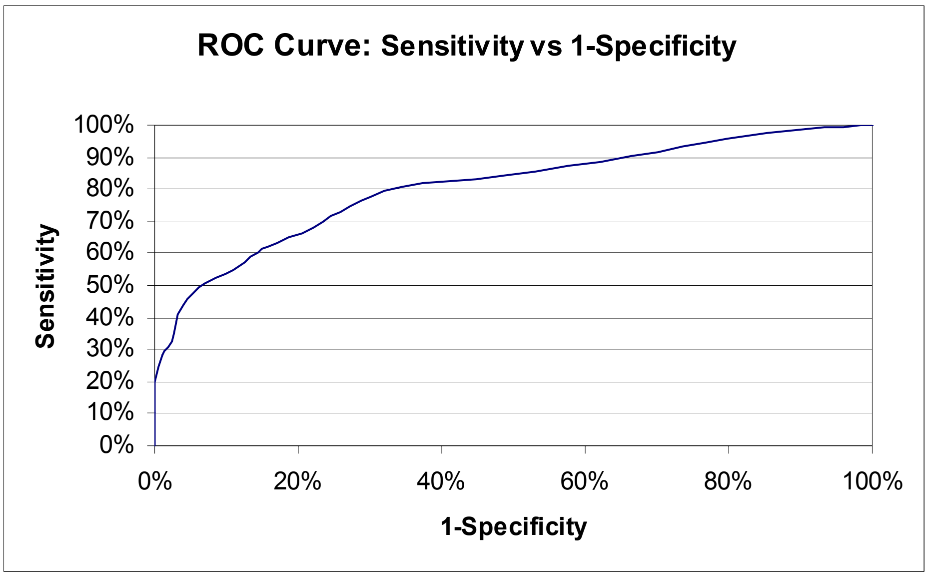

Figure 5.1 ROC curve estimated on the data used to estimate the logistic model

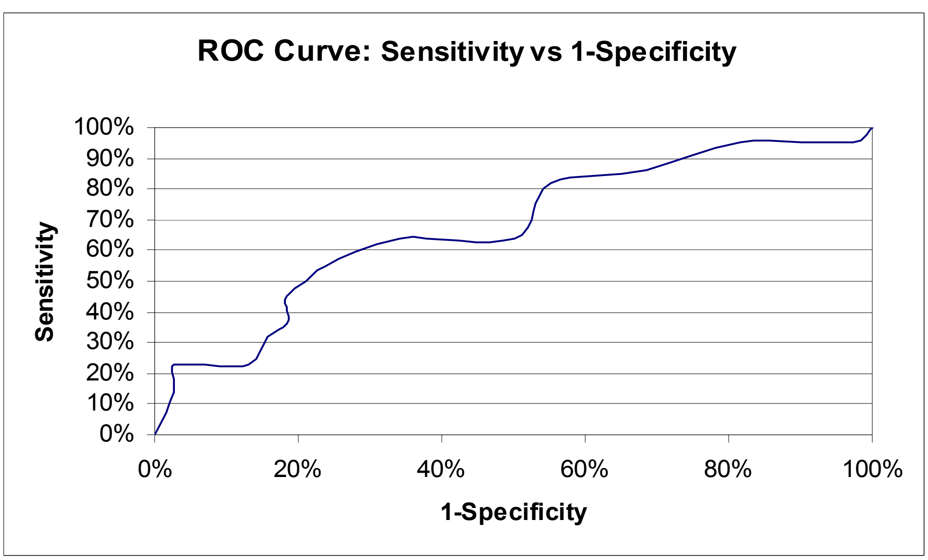

Figure 5.2 ROC curve estimated on the testing data

Checking linearity of the continuous variable:

Of the independent variables in this model, AGE is the only continuous variable. The assumed linearity of this variable was checked by introducing a Box-Tidwell transformation term, $x \ln x$, into the model and then fitting the model again. The Wald statistic for the coefficient of the transformation term is 0.808 and the corresponding *p*-value is 0.369, which is not significant at α=0.05 level. Therefore, the assumption that the continuous variable, AGE, is linear in the model is justified.

Checking interactions among covariates:

The next important step is determining whether there is evidence of interaction in the data. To be on the safe side, all possible interactions were checked in this study. Our main effects model contains five independent variables: housing type, whether an evacuation order was obtained, age, distance to the nearest body of water, and the marital status, and hence there are 10 possible pair-wise interactions. The results of adding each of the 10 interactions one at a time to the main effects model in Table 5.2 are presented in Table 5.5. However, the results show that none of the 10 possible interactions are significant at $\alpha = 0.05$ level. Therefore, we conclude that it is not necessary to include the interactions in the final model.

Table 5.5 Likelihood Ratio Test Statistic (G) and p-value for Possible Interactions of Interest When Added to the Main Effects Model in Table 5.2

Variable	df	Step 0			
		$-2LL_0$	$-2LL_{0+i}$	G	p-value
Main Effects Model		357.76			
ANDHOUS x MNEVCAND	2		356.904	0.856	0.663
ANDHOUS x CURRSWAT	2		356.601	1.159	0.569
ANDHOUS x MARITAL	4		356.166	1.594	0.807
ANDHOUS x AGE	2		356.656	1.104	0.587
MNEVCAND x CURRSWAT	1		356.329	1.431	0.238
MNEVCAND x MARITAL	2		354.034	3.726	0.155
MNEVCAND x AGE	1		356.480	1.280	0.262
CURRSWAT x MARITAL	2		356.312	1.448	0.488
CURRSWAT x AGE	1		357.760	0.000	0.999
MARITAL x AGE	2		354.805	2.955	0.223

Interpretation of the coefficients and the model:

In any linear regression model, the estimated coefficients for the independent variables represent the slope (i.e., rate of change) of a function of the dependent variable per unit of change in the independent variable. Similarly, in a logistic regression model, the slope coefficient represents the change in the logit corresponding to a change of one unit in the independent variable, i.e., $\beta_k = \dfrac{g(x_k+1)-g(x_k)}{(x_k+1)-x_k} = g(x_k+1)-g(x_k)$. To interpret this result, we need to use a measure of association termed the *odds ratio*. The odds ratio, denoted OR, is defined as the ratio of the odds for $x_k = 1$ to the odds for $x_k = 0$, and is given by:

$$OR = \frac{y(x_k=1)/[1-y(x_k=1)]}{y(x_k=0)/[1-y(x_k=0)]},$$

which approximates how much more likely (or unlikely) it is for the outcome to be present among those with $x = 1$ than among those with $x = 0$. Furthermore, since $y = \dfrac{e^{(\beta_0+\sum_j \beta_j x_j)}}{1+e^{(\beta_0+\sum_j \beta_j x_j)}}$,

$$OR_k = \frac{\left(\frac{e^{\beta_0+\beta_k}}{1+e^{\beta_0+\beta_k}}\right) \Big/ \left(\frac{1}{1+e^{\beta_0+\beta_k}}\right)}{\left(\frac{e^{\beta_0}}{1+e^{\beta_0}}\right) \Big/ \left(\frac{1}{1+e^{\beta_0}}\right)} = e^{\beta_k}$$

This relationship between the coefficient and the odds ratio is very important to interpret logistic regression models. For the final model shown in equation (5.1), the point and interval estimates of coefficients and odds ratios are listed in Table 5.6.

Table 5.6 Point and Interval Estimates of Coefficients and Odds Ratios

	β_k	e^{β_k} /OR_k	95% Confidence Interval of β_k	95% Confidence Interval of e^{β_k} /OR_k
ANDHOUS1	2.315	10.1	(1.03, 3.60)	(2.8, 36.6)
ANDHOUS2	-1.053	0.35	(-1.96, -0.144)	(0.14, 0.87)
MNEVCAND	1.444	4.2	(0.84, 2.04)	(2.3, 7.7)
AGE	-0.04	0.67*	(-0.06, -0.018)	(0.55, 0.84)*
CURRSWAT	0.801	2.2	(0.25, 1.35)	(1.28, 3.86)
MARITAL1	-1.255	0.29	(-2.31, -0.20)	(0.1, 0.82)
MARITAL2	-0.801	0.45	(-1.56, -0.044)	(0.21, 0.96)

* For the variable AGE, *OR*(10), i.e., odds ratio for an increase of 10 years in age, is calculated, for the change of 1 year in age may not be able to give a sufficient indication of the effect of the age on the dependent variable. Changes in multiples of 5 or 10 may be much more meaningful and easily understood.

From Table 5.6, it can be seen that the sign of each coefficient in the model is intuitively sensible. The positive sign of the coefficient for ANDHOUS1 indicates a household living in a mobile dwelling unit is more likely to evacuate than a household living in a multi-family building (like an apartment building); this is reasonable as mobile homes are generally much more vulnerable than multi-family buildings to wind damage. The negative sign of the coefficient for ANDHOUS2 indicates a household living in a single family house is less likely to evacuate than a household living in a multi-family building; this may be due to the fact that persons living in multi-family buildings are likely to be more mobile than larger household units in single family houses. MNEVCAND has a positive sign in its coefficient, which indicates a household is more likely to evacuate if it gets a mandatory evacuation order than when no evacuation order is given; this is obviously a reasonable indication. The negative sign for AGE indicates a household is less likely to evacuate if the head or the influential member of the household is older; to reveal the reason for this phenomenon needs in-depth surveys, but it is expected that it reflects the fact that older people dislike leaving their home more than younger people and because they are generally less mobile. The positive sign for CURRSWAT indicates a household is more likely to evacuate if it lives closer to a body of water; this indication is reasonable because households living closer to water may perceive that they are more likely or easily to get flooded in a hurricane. Both MARITAL1 and MARITAL2 have a negative sign, which indicates that, compared with those who are separated, divorced, or widowed, those that are single, married, or living with partners are less likely to evacuate. The reasons for this phenomenon could be as follows: Singles are more aggressive and have no family to be concerned with in a hurricane, and therefore they are less likely to leave. The married and those living with partners could have mental and physical support from their spouses or partners and therefore are less likely to evacuate than the separated, divorced, or widowed who relatively lack support. Therefore, the indication of the signs is also reasonable.

The values in Table 5.6 are interpreted as follows:

1) Housing type:

a. Compared with those who live in a multi-family building (referred to as *reference cell*), those living in mobile homes are on average 10.1 times as likely to evacuate, according to the estimated $O\hat{R} = e^{2.315} = 10.1$. The confidence interval suggests that those living in mobile homes could be as little as 2.8 or as much as 36.6 times likely to evacuate as those living in multi-family buildings, at the 95% level of confidence.

b. Compared with those who live in a multi-family building, those living in a single-family house are in average 0.35 times as likely to evacuate ($O\hat{R} = e^{-1.053} = 0.35$). The confidence interval suggests that those living in single-family house could be as little as 0.14 or much as 0.87 times likely to evacuate as those living in multi-family buildings, at the 95% level of confidence.

2) Mandatory evacuation order:

a. Compared with those who do not receive a mandatory evacuation order, those who receive a mandatory evacuation order are on average 4.2 times as likely to evacuate, according to the estimated $O\hat{R} = e^{1.444} = 4.2$. The confidence interval suggests that those receiving an evacuation order could be as little as 2.3 or much as 7.7 times likely to evacuate as those not receiving an evacuation order, at the 95% level of confidence.

3) Distance from the household to the nearest body of water:

a. Those living within one mile to water are on average 2.2 times ($O\hat{R} = e^{0.801} = 2.2$) as likely to evacuate as those who live farther than one mile. The confidence interval suggests that the former could be as little as 1.28 or much as 3.86 times more likely to evacuate as the latter, at the 95% level of confidence.

4) Marital status of the respondent:

a. Singles are on average 0.29 times as likely to evacuate as those who are separated, divorced, or widowed, according to the estimated $O\hat{R} = e^{-1.255} = 0.29$. This number could vary to as little as 0.1 or as much as 0.82, at the 95% level of confidence.

b. The married and those living with their partners are in average 0.45 times ($\hat{OR} = e^{-0.801} = 0.45$) as likely to evacuate as those separated, divorced, or widowed. The confidence interval suggests that the former could be as little as 0.21 or much as 0.96 times to evacuate as the latter, at the 95% level of confidence.

5) Age of the respondent:

a. The estimated odds ratio for an increase of 10 years in age is $\hat{OR}(10) = e^{-0.04\times10} = 0.67$. This indicates that for every increase of 10 years in age, the probability of evacuation decreases by 0.67 times on average. This number could vary to as little as 0.55 or as much as 0.84, at the 95% level of confidence.

Intuitively, the above interpretation is sensible, which indicates that the sign and the value of each coefficient in the model are correct.

5.2 Neural Network Models

5.2.1 Back-propagation Neural Network (BPNN) Model

Similar to the development of the logistic regression model, the criterion for the selection of k in the BPNN model is to maximize the average of sensitivity and specificity, as sensitivity and specificity are considered of similar importance. With model specification 1, it was observed that the average of the sensitivity and specificity on the training data reached the maximum, 78.58%, when $k = 0.37$. The percent correctly predicted by the BPNN model on the training data and the testing data are shown in Table 5.7 and Table 5.8, respectively. From the tables, it can be observed that, on the training data, 76.87% of the households who evacuated and 80.3% of the households who did not evacuate were correctly predicted by the model, which produces an overall percent correctly predicted of 78.86%. On the testing data, 68.18% of the households who evacuated and 63.16% of the households who did not evacuate were correctly predicted by the model, and the overall percent correctly predicted is 65%.

Table 5.7 Percent correctly predicted by the BPNN model with specification 1 on the estimation data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted	Average of Sensitivity and Specificity
		Evacuated	Not			
Observed	Evacuated	113	34	76.87% (113/147)	78.86% (276/350)	78.58%
	Not	40	163	80.3% (163/203)		

Table 5.8 Percent correctly predicted by the BPNN model with specification 1 on the testing data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted	Average of Sensitivity and Specificity
		Evacuated	Not			
Observed	Evacuated	15	7	68.18% (15/22)	65% (39/60)	65.67%
	Not	14	24	63.16% (24/38)		

With model specification 2, it was observed that the average of the sensitivity and specificity on the training data reached the maximum, 83.94%, when $k = 0.4$. Percents correctly predicted by the model on the training data and the testing data are shown in Table 5.9 and Table 5.10, respectively. From the tables, it can be observed that, on the training data, 78.23% of the households who evacuated and 89.66% of the households who did not evacuate were correctly reproduced by the model, which produces an overall percent correctly predicted of 84.86%. On the testing data, 50% of the households who evacuated and 71.05%

of the households who did not evacuate were correctly predicted by the model, and the overall percent correctly predicted is 60.5%.

Table 5.9 Percent correctly predicted by the BPNN model with specification 2 on the estimation data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted	Average of Sensitivity and Specificity
		Evacuated	Not			
Observed	Evacuated	115	32	78.23% (115/147)	84.86% (297/350)	83.94%
	Not	21	182	89.66% (182/203)		

Table 5.10 Percent correctly predicted by the BPNN model with specification 2 on the testing data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted	Average of Sensitivity and Specificity
		Evacuated	Not			
Observed	Evacuated	11	11	50% (11/22)	63.33% (38/60)	60.53%
	Not	11	27	71.05% (27/38)		

Using model specification 1, two Receiver Operating Characteristic (ROC) curves estimated on the training data and the testing data are shown in Figures 5.3 and 5.4 respectively. As shown in Figure 5.3, the area under the ROC curve estimated on the training data is 0.83, indicating the model has excellent discrimination. The area under the ROC curve estimated on the testing data is 0.71 (Figure 5.4), indicating a good discrimination.

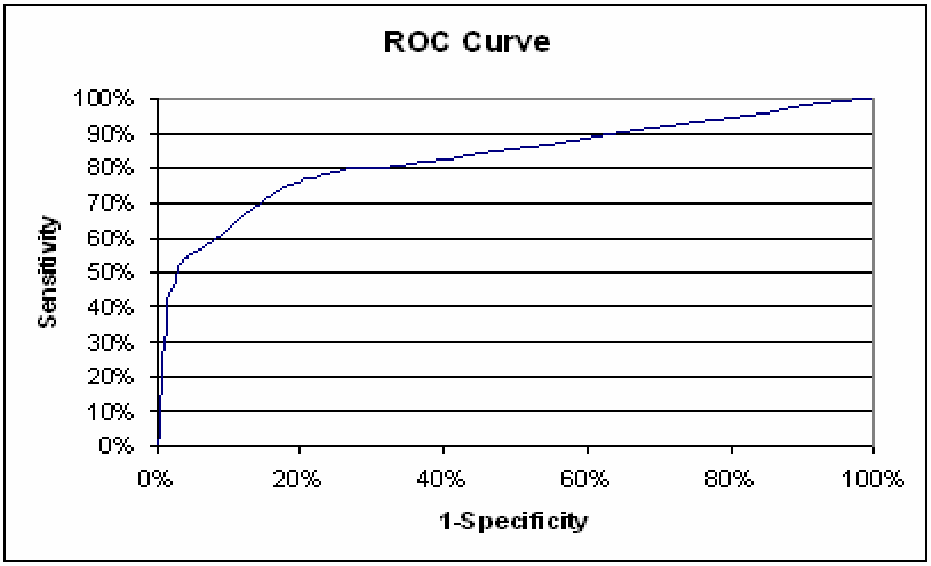

Figure 5.3 ROC curve estimated on the training data with model specification 1

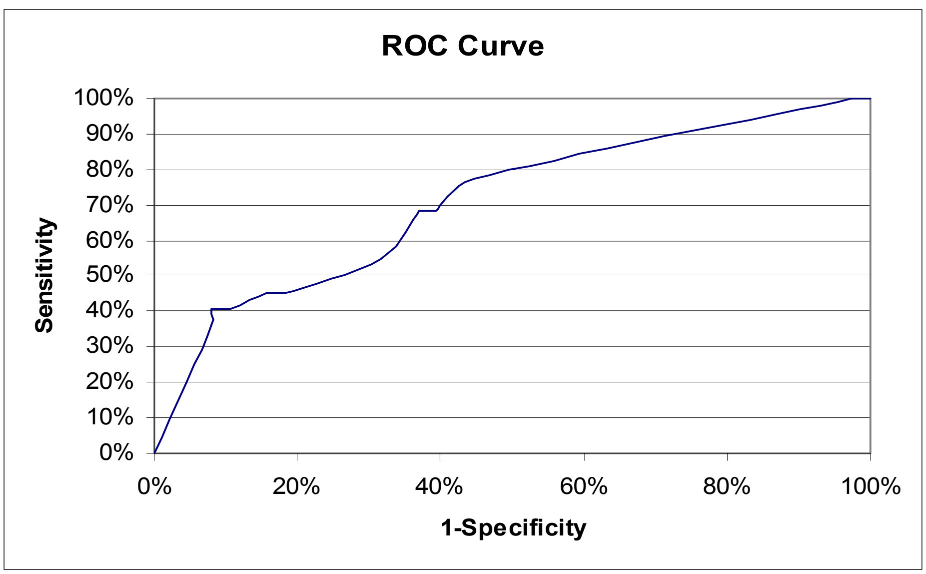

Figure 5.4 ROC curve estimated on the testing data with model specification 1

Using model specification 2, two Receiver Operating Characteristic (ROC) curves estimated on the training data and the testing data are shown in Figures 5.5 and 5.6 respectively. As shown in Figure 5.5, the area under the ROC curve estimated on the training data is 0.898, indicating the model has excellent discrimination. The area under the ROC curve estimated on the testing data is 0.65 (Figure 5.4), a fair discrimination.

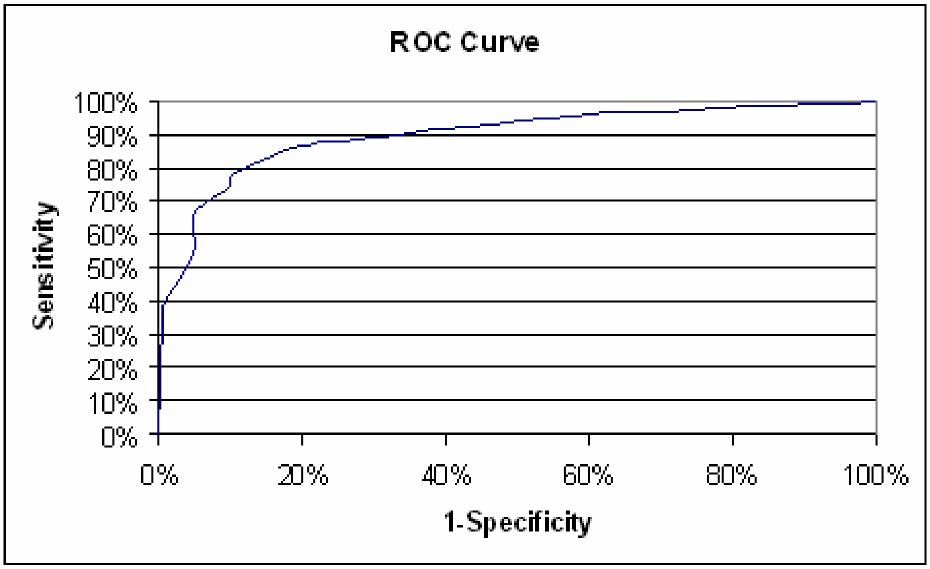

Figure 5.5 ROC curve estimated on the training data with model specification 2

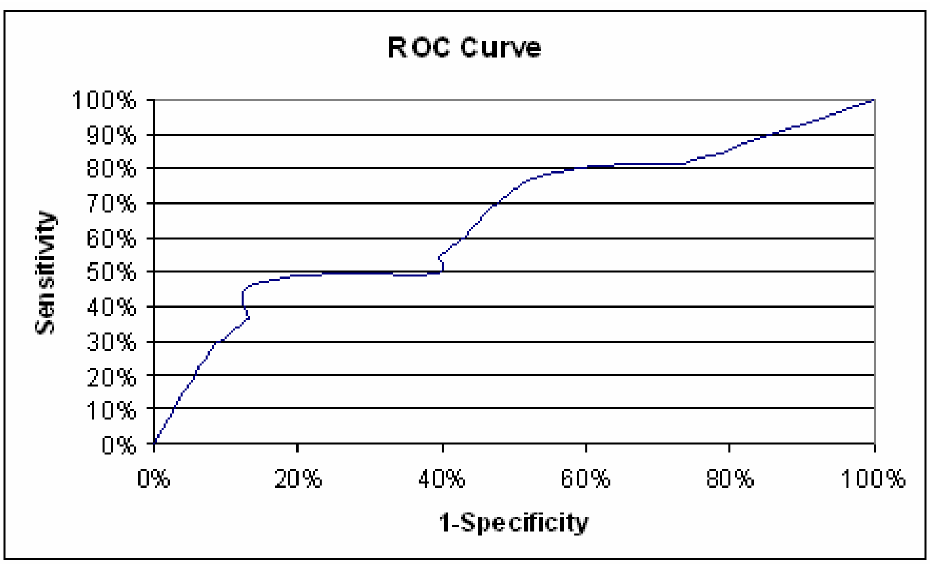

Figure 5.6 ROC curve estimated on the testing data with model specification 2

Assessed on the ROC curves estimated on the training data, both BPNN model 1 and model 2 have excellent discrimination ability. Model 1 performs a little better on the testing data than model 2. Taking into account the model parsimony, model specification 1 is preferred again. Compared with the logistics regression model, BPNN model 1 also has stronger discrimination.

5.2.2 Probabilistic Neural Network (PNN) Model

Tables 5.11 and 5.12 show the percent correctly predicted by the PNN model with model specification 1 on the training data and the testing data respectively. From the tables, it can be observed that, on the training data, 93.2% of the households who evacuated and 100% of the households who did not evacuate were correctly predicted by the model, which produces an overall percent correctly predicted of 97.14%. However, on testing data, only 54.5% of the households who evacuated and 76.3% of the households who did not evacuate were correctly predicted by the model, and the overall percent correctly predicted is 68.33%.

Tables 5.13 and 5.14 show the percents correctly predicted by the PNN model with model specification 2 on the training data and the testing data respectively. From the tables, it can be observed that, on the training data, 88.4% of the households who evacuated and 98% of the households who did not evacuate were correctly reproduced by the model, which produces an overall percent correctly predicted of 94%. However, on testing data, again 54.5% of the households who evacuated and 81.6% of the households who did not evacuate were correctly predicted by the model, and the overall percent correctly predicted is 71.67%.

Table 5.11 Percent correctly predicted by PNN model with specification 1 on the training data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	137	10	93.2% (137/147)	97.14% (340/350)
	Not	0	203	100% (203/203)	

Table 5.12 Percent correctly predicted by PNN model with specification 1 on the testing data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	12	10	54.5% (12/22)	68.33% (41/60)
	Not	9	29	76.3% (29/38)	

Table 5.13 Percent correctly predicted by the PNN model with specification 2 on the training data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	130	17	88.4% (130/147)	94% (329/350)
	Not	4	199	98.0% (199/203)	

Table 5.14 Percent correctly predicted by the PNN model with specification 2 on the testing data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	12	10	54.5% (12/22)	71.67% (43/60)
	Not	7	31	81.6% (31/38)	

The following conclusions are drawn based on the results produced by the models:

1) The Probabilistic Neural Networks can model this specific problem well, according to the overall PCPs of around 70% estimated on testing data.
2) The network can learn extremely well from the data presented to it, but its generalization ability is not as good as its learning ability, as we can see from the substantial difference between the PCPs on the training data and those on the testing data.
3) Model specification 1 is preferred to model specification 2. Though improvements with specification 2 were observed based on the PCPs on the testing data, the improvements are very marginal and the parsimony and the relative ease of variable acquisition of specification 1 are more attractive. A closer inspection also reveals that there is no improvement in PCPs for the group of evacuated households; as we know, this is more important for evacuation planning.

5.2.3 Learning Vector Quantizer (LVQ) Model

Tables 5.15 and 5.16 show the percent correctly predicted by the LVQ model with model specification 1 on the training data and the testing data respectively. From the tables, it can be observed that, on the training data, 66.7% of the households who evacuated and 82.8% of the households who did not evacuate were correctly predicted by the model, which produces an overall percent correctly predicted of 76%. On the testing data, only 45.5% of the households who evacuated and 76.3% of the households who did not evacuate were correctly predicted by the model, and the overall percent correctly predicted is 65%.

Tables 5.17 and 5.18 show the percent correctly predicted by the LVQ model with model specification 2 on the training data and the testing data respectively. From the tables, it can be observed that, on the training data, 88.4% of the households who evacuated and 98% of the households who did not evacuate were correctly predicted by the model, which produces an overall percent correctly predicted of 94%. However, on testing data, again 54.5% of the households who evacuated and 81.6% of the households who did not evacuate were correctly predicted by the model, and the overall percent correctly predicted is 71.67%.

Table 5.15 Percent correctly predicted by the LVQ model with specification 1 on the training data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	98	49	66.7% (98/147)	76% (266/350)
	Not	35	168	82.8% (168/203)	

Table 5.16 Percent correctly predicted by the LVQ model with specification 1 on the testing data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	10	12	45.5% (10/22)	65% (39/60)
	Not	9	29	76.3% (29/38)	

Table 5.17 Percent correctly predicted by the LVQ model with specification 2 on the training data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	91	56	61.9% (91/147)	76% (266/350)
	Not	28	175	86.2% (175/203)	

Table 5.18 Percent correctly predicted by the LVQ model with specification 2 on the testing data

		Predicted		Percent Correctly Predicted	Overall Percent Correctly Predicted
		Evacuated	Not		
Observed	Evacuated	11	11	50% (11/22)	70% (42/60)
	Not	7	31	81.6% (31/38)	

The following conclusions are drawn based on the results produced by the models:

1) The LVQ models can model this specific problem well, according to the overall PCPs of 65% and 70% on testing data.
2) The generalization ability of the model is good as it can produce reasonably good PCPs on the testing data, which are not much lower than the PCPs estimated on the training data.
3) Model specification 1 is preferred to model specification 2. Though improvements with specification 2 were observed based on the PCPs estimated on the testing data, the improvements are marginal and the parsimony and the relative ease of variable acquisition of specification 1 are more attractive.

5.3 Summary of the New Models

A summary of the statistics of the developed models with specification 1 is shown in Table 5.19.

Table 5.19 Summary of the Statistics of the Models

		ρ^2	Hosmer-Lemeshow test (p-value)	Likelihood-ratio test (p-value)	The area under ROC curve	PCP		
						Evacu-ating	Not Evacu-ating	Over-all
On Training/ Calibrating Data (350 cases)	Logistic regression model	0.25	0.485	<0.001	0.81	74.2%	73.9%	74%
	BPNN model	-	-	-	0.83	76.9%	80.3%	78.9 %
	PNN model	-	-	-	-	93.2%	100%	97.1 %
	LVQ model	-	-	-	-	66.7%	82.8%	76%
On Testing Data (60 cases)	Logistic regression model	-	-	-	0.68	63.6%	68.4%	66.7 %
	BPNN model	-	-	-	0.71	68.2%	63.2%	65%
	PNN model	-	-	-	-	54.5%	76.3%	68.3 %
	LVQ model	-	-	-	-	45.5%	76.3%	65%

5.4 PBS&J Southwest Louisiana Trip Generation Model of Hurricane Evacuation

PBS&J (2000) conducted studies on hurricane evacuation travel demand modeling for Southwest Louisiana. The trip generation model was developed using the cross-classification procedure. Three independent variables were used in the model to estimate evacuation rates for evacuation zones. These included hurricane intensity, housing type, and the evacuation zone itself which implicitly indicates the location of the evacuation zone and whether it was vulnerable to flooding or other storm damage. Hurricane intensity was classified into five storm scenarios ranging from Scenario A through Scenario E, referring to Categories 1 through 5 of hurricanes on the Saffir-Simpson Scale, respectively. Housing types included permanent units, mobile units, and tourist units. Evacuation zones were categorized by the study team before they were used as a variable in the model. Typically, a parish consists of several evacuation zones. The guidelines for the delineation of evacuation zones included (PBS&J, 2000e):

a) Zones should relate to maximum potential surge flooding limits for each storm scenario.
b) Zones should relate well to census data base unit.
c) Zonal boundaries should include identifiable natural features, roadways, landmarks, etc.
d) Small "pocket" zones that would be isolated by surrounding surge should be avoided.
e) Zones should be able to be served by major evacuation routes.

Therefore, the evacuation zone itself implicitly represents a combination of a few factors, mainly including the geographic location of the zone and the vulnerability of the zone to flooding. Evacuation zones were also classified according to their vulnerability to storm intensity: For instance, an evacuation zone is called a Scenario C Evacuation Zone if all people living in the permanent housing units in that zone are expected to evacuate in a storm of Scenario C or stronger but few evacuate in a storm weaker than Scenario C. Zones which are expected to generate few evacuees from permanent housing units (less than 10%) even under storm Category 5 are called Inland Evacuation Zones.

The following assumptions were made regarding the trip production model developed by PBS&J (2000e):

1) All persons living in areas flooded by storm surge should be evacuated. This evacuee group included permanent residents living in single-family, multi-family, or mobile home units, as well as tourists staying in seasonal housing units located in storm surge vulnerable areas.

2) All mobile home residents living outside the hurricane flooded areas but still in a vulnerable area were assumed to evacuate due to high wind vulnerability.

3) A small percentage (1 to 5% depending on storm intensity) of the non-vulnerable population was assumed to evacuate their dwelling units.

A sample of the PBS&J model is shown in Appendix B. The number in each cell of the cross-classification table is the evacuation rate for the zone under the corresponding storm scenario and for the corresponding housing type. These numbers can also be interpreted as the average probability that people in each category of housing type and flooding potential (which is implicitly represented by the evacuation zone) would evacuate under each storm scenario.

The performance of the PBS&J model was analyzed at both aggregate and disaggregate levels. Since the PBS&J model was not developed on the data employed in this study, the entire data set, including the training and the testing data sets were used to test the performance of the PBS&J model. The PBS&J model provides evacuation rates for evacuation zones; for analysis at aggregate level, the evacuation rate for each parish was computed by averaging all zone rates weighted by the number of dwelling units in each zone and in each housing type. The Scenario C evacuation rates were used here because Andrew was a Category 3 hurricane. The overall evacuation rate for the whole study area was also computed by aggregating zone evacuation rates in the same way as above. The computed evacuation rates for all the parishes and the whole study area are shown in Table 5.20. By comparison with the observed values, error statistics such as Percentage Error (PE) and Mean Absolute Percentage Error (MAPE) were calculated and are also shown in Table 5.20.

Table 5.20 Evaluation of the PBS&J model

	Evacuation Rate		
	PBS&J model	Observed	Percentage Error*
Cameron	100%	100%	0
Calcasieu	65.8%	30.1%	+118%
Jefferson Davis	37.2%	14.3%	+160%
Vermillion	66.5%	75%	-11.3%
Acadia	54.3%	34.6%	+56.9%
Lafayette	14.8%	22.6%	-34.5%
Iberia	98.6%	57.9%	+70%
Iberville	44.7%	40%	+12%
St. Martin	43.6%	73.3%	-40.5%
Terrebonne	100%	42.9%	+133%
St. Mary	100%	90.3%	+11%
Assumption	87.7%	40%	+119%
MAPE			**64%**
Overall Evacuation Rate	54%	42.5%	27%

*Percentage Error is defined as (estimated value – observed value) / observed value × 100%.

From Table 5.20, we find that the PBS&J model does a fair job in predicting the evacuation rate of the evacuation zones. The evacuation rates of five parishes were estimated with an error within 50% of the observed value. The highest deviation was 160% of the observed value for Jefferson Davis Parish and the lowest -40.5% for St. Martin Parish. The mean absolute percentage error (MAPE) of the estimated values in relation to the observed values was 64%. This error is moderate and acceptable considering there is more uncertainty in the emergency setting. The estimated whole area evacuation rate is 54%, 27% higher than the actual evacuation rate, indicating that the model overestimates evacuees.

Analysis at disaggregate level employed the evacuation rates of the evacuation zones under storm Scenario C of the PBS&J model, because the evacuation rates can also be interpreted as the average probability that households in each category of housing type and flooding potential (which is implicitly represented by the evacuation zone) would evacuate.

Using the PBS&J model, each household was assigned a probability based on its housing type and the evacuation zone where the household was located. The mean of the estimated probabilities for all the households and the root mean square error (RMSE) of the estimated probabilities in relation to the observed values were computed, which were 60.3% and 58.8% respectively. The MAPE was not used in this case because the percentage error (PE) cannot be calculated for those households who did not evacuate and therefore had an observed evacuation probability of 0.

5.5 Model Comparison

5.5.1 Comparison of the Models

To provide a level playing field to evaluate the models, only the testing data were used for all the models, including the PBS&J model. First, the probability that the households would evacuate was estimated by each of the models. Then for each model, the mean of the estimated probabilities for all the households and the root mean square error (RMSE) of the estimated probabilities in relation to the observed values were computed. The results are shown by model in Table 5.21. From the table, we can see that the PBS&J model produced a new mean and a new RMSE on the testing data, which are both slightly different from the ones computed on the entire data set. Difference was also observed of the mean of observed probability in this table from that in Table 5.20; this is also because the former was computed only on the testing data while the latter was on the entire data set.

Table 5.21 Comparison of the PBS&J model and the models developed in this study

	Observed	PBS&J Model	Logistic Regression Model	BPNN Model	PNN Model	LVQ Model
Mean of Evacuation Probabilities	36.7%	55.5%	41.1%	44.5%	35%	31.7%
Root Mean Square Error (RMSE)		62.5%	47.7%	47.9%	56.3%	59.2%

From Table 5.21, we find that the PBS&J model, logistic regression model, and the BPNN model produced means greater than the observed, while the PNN model and the LVQ model gave lower means. This indicates that the former three models overestimate the number of evacuees while the latter two underestimate the number. To some extent, overestimation is preferred to underestimation for emergency preparedness. However, it should be realized that aggregation (averaging in this case) of the results from a disaggregate model can cancel out the errors in the results, and therefore the mean is not a sufficient measure for model comparison.

Instead, the RMSE which summarizes the overall accuracy provided by the model is a good statistic for model comparison. The closer the predictions $\hat{y}_i$ are to the actual values y_i, the more accurate the forecasting model is, which is indicated by a lower RMSE. Assessed on the RMSE values, the logistic regression model and the BPNN model produced the closest predictions to the actual values of evacuation probability. This is indicated by their RMSE values of 47.7% and 47.9% respectively. The RMSE produced by the PNN model and the LVQ model was 56.3% and 59.2% respectively, which are considerably higher than those of the logistic regression model and the BPNN model. However, of all the models, the PBS&J model produced the highest RMSE of 62.5%.

The comparison between the models developed in this study was also conducted based on the statistics in Table 5.19. It can be found that all the models developed in this study performed well in predicting evacuation trips. The overall PCPs estimated on the testing data are all within the range between 65% and 68.3%. On the training data, the PNN model produced an overall PCP as high as 97% and the others also produced values between 74% and 79%. However, in spite of the fact that the overall PCPs on the testing data are very close to one another, the logistic regression model and the BPNN model are considered better, because these two models produced high sensitivity as well as high specificity on both the calibrating / training data and the testing data. This indicates that the two models have a stronger ability to discriminate between those subjects who experience the outcome of interest versus those who do not, which is very desirable in an emergency setting. On the other hand, although the PNN model performed the best in reproducing the training data, the lower sensitivity prediction on the testing dataset jeopardizes its ability to accurately predict who will evacuate. Similarly, the LVQ model produced lowest sensitivities on both the training and the testing data (66.7% and 45.5% respectively).

5.5.2 Conclusions

From the above analysis and comparison, it is found that the PBS&J model just did a fair job and the logistic regression and ANN models developed in this study are better than the cross-classification type PBS&J model in modeling this specific problem. More significant variables included in the logistic regression and ANN models should account for the improvement at least partly.

However, it should be realized that the cost to run these models is higher than that to run the PBS&J model as these models need more inputs. The hurricane evacuation travel demand models developed by PBS&J are based on extensive data on evacuation behavior of people in hurricane affected areas at different locations with different hurricane intensity. The models are therefore ready for application in various hurricane situations.

It is also found that all the models developed in this study performed virtually equally well, although a closer investigation found that the logistic regression and BPNN models are slightly better than the PNN and LVQ models.

Artificial neural networks have the ability to simulate observed evacuation behavior and learn directly from the data without having to specify the functional form of the relationship between the dependent variable and the independent variables. The results obtained above demonstrate their ability to model evacuation behavior well. Their weakness lies in the difficulty of assessing the internal operation of the networks and the uncertainty regarding the validity of the model beyond the limits of the training data. In addition, the statistical measures for assessing the performance of ANN models are limited.

On the other hand, the process of the development of the logistic regression model is transparent. Each step can be well controlled and traced. The model can be assessed by a number of statistical measures, which makes the model developer and user more assured. However, the specified functional form and the assumed linearity and addition could limit the model to explain the data.

CHAPTER 6
SUMMARY AND CONCLUSIONS

6.1 Summary of Model Development and Comparison

Estimation of evacuation trips to be generated in a hurricane is a critical step for emergency preparedness. So far, few studies have addressed the issue of modeling trip generation of hurricane evacuation traffic. This study was conducted to develop hurricane evacuation trip generation models and test the performance of these models. The models related a household's decision to evacuate to factors describing the household and the conditions surrounding the household during the storm. The factors used included housing type, surrounding geography of the household, household socioeconomic features, and action of public authorities. Because data from a specific hurricane were used in this research, the characteristics of the hurricane itself could not be used to interpret people's decision to evacuate. Logistic regression and artificial neural networks (ANNs) techniques were applied to develop models. Artificial neural network models were developed with two model specifications, and performance of the models with different model specifications was analyzed and compared with each other. The models developed in this study were also compared with a cross-classification type model developed by consultants to estimate trip generation in Southwestern Louisiana (PBS&J, 2000d).

In this study, the data from the southwest Louisiana post-Andrew household survey were used to estimate the models and also test the performance of the models in being able to reproduce evacuation data on a separate test data set. Due to missing data, 410 households with complete information were finally used for modeling. These 410 households were divided into an estimation data set of 350 households and a testing data set of 60 households. The logistic regression and ANN (back-propagation neural network, probabilistic neural network, and learning vector quantizer) models of evacuation trip generation were estimated and then used to predict the decision of the households on the test data set where actual decisions were known. The logistic regression and BPNN models tell how likely a household will evacuate, while the PNN and LVQ models directly identify whether the household will evacuate or not.

To assess the performance of the logistic regression model, statistical measures such as ρ^2, the Hosmer-Lemeshow statistic, and likelihood-ratio statistic, and the area under ROC curve were computed. The discrimination of ANN models was assessed by computing the ROC curve for the BPNN model and the classification tables (i.e., PCPs) for the PNN and LVQ models.

The performance of the PBS&J model was assessed on the entire data set. However, to provide a level playing field, the comparison of the models was conducted on the testing data only. MAPE and RMSE were computed for model assessment and comparison.

6.2 Summary of Results and Analyses

The value of ρ^2 and the Hosmer-Lemeshow statistic showed the logistic regression model did fit the data well, and the likelihood-ratio statistic indicated the logistic regression model is significant at 99.9% level of confidence. Both the logistic regression model and the BPNN model have excellent discrimination according to the ROC curves computed from classification tables. The PNN and LVQ models developed in this research proved to be well suited for this problem based on the PCPs estimated on the testing data set.

The independent variables which were found to be significant in explaining households' evacuation behavior include housing type, whether the household gets mandatory evacuation order, age of the respondent, distance from the household to the closest body of water, and marital status of the respondent. Other variables, including ownership of the residence, hurricane experience of the household, race, education level of the respondent, and household size, were tested for inclusion, but they were found to add very little to the explanatory power of the models. Therefore, the model specification consisting of the five significant variables is considered better as it gives a more parsimonious model that still explains the data no worse.

Comparison between the model predictions and the actual values showed that the logistic regression model, the BPNN model, and the PBS&J model overestimated the number of evacuees while the PNN model and the LVQ model underestimated the number. Assessed on the values of RMSE estimated on the testing data, the logistic regression model and all the ANN models produced closer predictions to the observed values than the PBS&J model did on this specific problem.

The values of RMSE also indicated that the logistic regression model and the BPNN model produced closer predictions to the actual values than the PNN and LVQ models. Assessed on the PCPs, the logistic regression and BPNN models gave higher sensitivity than the PNN and LVQ models, although the overall PCPs were all very close to each other.

6.3 Conclusions

Based on the results and analyses reported above, conclusions of this study are drawn as follows:

1) This study demonstrated the feasibility of using logistic regression and ANNs in predicting households' decision to evacuate during a hurricane.
2) All the models developed in this study are better than the PBS&J model in predicting households' evacuation trip generation in southwestern Louisiana.
3) Though the models developed in this study are more expensive to use than the PBS&J model as they require more inputs to make predictions, improved accuracy in prediction should be worth the extra cost, as inaccurate forecasts will lead to either under-preparedness which may cause more injuries and fatalities or over-preparedness which wastes money and manpower.
4) All the models developed in this study displayed similar predictive performance, although the logistic regression and BPNN models are considered slightly better than the PNN and LVQ models.
5) The fact that the ANN models performed no better than the logistic regression model indicates that the general advantages of ANN modeling do not guarantee better models to be produced for any specific problems.
6) The comparison of different model specifications indicated that the accuracy of the model rely completely on those independent variables which have significant association with the dependent variable. The contributions of those insignificant variables were very marginal.
7) The limitations of the models developed in this study include:
    i. The models were developed on one data set only. It is therefore difficult to draw a generalized conclusion whether logistic regression and ANN models are always better than the cross-classification type model used by PBS&J.

ii. The data used in this study is only associated with one category of hurricane intensity, Category C. Therefore, hurricane intensity was not able to be included in the independent variable set, although it does have significant effect on people's evacuation decision.

iii. Locations of the households in the data set are not precise enough. Only the city or town rather than the address of the household was provided. This made it difficult to know whether the household was located in a flood zone or not. This uncertainty prevented being able to discern whether the household being in a flood zone was a significant independent variable in the models or not.

6.4 Opportunities for Future Research

The opportunities for future research are identified as follows:

1) More data which cover the full range of hurricane intensity shall be employed for the development of trip generation models of hurricane evacuation. Thus, hurricane intensity can be used as an independent variable in the model, which can enhance explanatory power of the model and make the model applicable to different situations.
2) Comparison of different model types as well as different models developed on extensive data can be conducted, and the results can be generalized regarding model type, model specification, and influential factors. This can benefit the development of models in the future.
3) Study and model hurricane evacuation trip generation characteristics of transient populations. This is particularly important for some coastal areas which attract many tourists every year in summer, the time when hurricanes are most likely to happen. It

is believed that transient populations have different evacuation characteristics from permanent residents.

4) Spatial and temporal transferability of hurricane evacuation trip generation models is also a promising research field. The existing techniques which were developed in the studies of transferability of urban trip generation models can be tested in emergency settings and modified or improved if necessary.

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APPENDIX A

DEFINITION OF VARIABLES AND DESIGN OF DUMMY VARIABLES

A.1 Definition of Variables

Variable	Definition
ANDHOUS	Housing type, divided into three groups: 1) mobile home, 2) single-family house, and 3) multi-family building.
MNEVCAND	Whether the household gets a mandatory evacuation order, divided into two groups: 1) get, and 2) not get.
AGE	The age of the respondent
CURRSWAT	Distance from the household to the nearest body of water, divided into two groups: 1) ≤ 1 mile, and 2) > 1 mile.
MARITAL	Marital status of the respondent, divided into three groups: 1) single and never married, 2) married or living with partner, and 3) separated, divorced, or widowed.
MARITAL2_Only	Marital status of the respondent, divided into two groups: 1) married or living with partner, and 2) other.
OWNRES	Ownership of the residence: 1) owned, and 2) rented or other.
HUREXPAN	Hurricane experience before Andrew: 1) having experience, and 2) no experience.
PHURRSEV	Hurricane experience before Andrew, divided into three groups: 1) yes and the hurricane(s) destroyed or severely damaged people's houses, 2) yes but the hurricane(s) didn't destroy or severe damaged people's houses, and 3) no experience.
DISTWAT	Distance from the household to the nearest body of water, divided into four groups: 1) on the waterfront, 2) not on waterfront but within one block of water, 3) more than one block of water but within one mile, and 4) more than one mile.
RACE1_Only	Race: 1) white, and 2) other.
RACE2_Only	Race: 1) Black, and 2) other.
HHSIZE	Household size of the respondent
EDUCAT	Education level of the respondent, divided into four groups:1) 8^{th} grade or less, 2) > 9^{th} grade but ≤ High school, 3) > High school but ≤ College (Bachelor Degree), and 4) > College (Bachelor Degree) but ≤ Graduate Degree
FLOODZON	Whether the household is in a flood zone: 1) Yes, and 2) No.

A.2 Design of Dummy Variables

1) Housing type:

Housing Type	Dummy Variables	
	ANDHOUS1	ANDHOUS2
Mobile home	1	0
Single-family house	0	1
Multi-family building	0	0

2) Whether the household gets a mandatory evacuation order:

Whether the household gets a mandatory evacuation order	Dummy Variable
	MNEVCAND
Yes	1
NO	0

3) Distance from the household to the nearest body of water:

Distance from the household to the nearest body of water	Dummy Variable
	CURRSWAT
<= 1 mile	1
> 1 mile	0

OR

Distance from the household to the nearest body of water	Dummy Variables		
	DISTWAT1	DISTWAT2	DISTWAT3
On the waterfront	1	0	0
Not on waterfront but within one block of water	0	1	0
More than one block of water but within one mile	0	0	1
More than one mile	0	0	0

4) Marital status:

Marital Status	Dummy Variables	
	MARITAL1	MARITAL2
Single and never married	1	0
Married or living with partner	0	1
Separated, divorced, widowed	0	0

OR

Marital Status	Dummy Variable
	MARITAL2_Only
Married or living with partner	1
Other	0

5) Ownership of the residence:

Ownership of the residence	Dummy Variable
	OWNRES
Owned	1
Rented or other	0

6) Hurricane experience:

Hurricane experience before Andrew	Dummy Variable
	HUREXPAN
Yes	1
No	0

OR

Hurricane experience before Andrew	Dummy Variables	
	PHURRSEV1	PHURRSEV2
Yes and the hurricane(s) destroyed or severely damaged people's houses	1	0
Yes but the hurricane(s) didn't destroy or severe damaged people's houses	0	1
No experience	0	0

OR

Hurricane experience before Andrew	Dummy Variable
	PHURRSEV1_Only
Yes and the hurricane(s) destroyed or severely damaged people's houses	1
Other	0

7) Race:

Race	Dummy Variables	
	Race1	RACE2
White	1	0
Black	0	1
Other	0	0

OR

Race	Dummy Variable
	RACE1_Only
White	1
Other	0

OR

Race	Dummy Variable
	RACE2_Only
Black	1
Other	0

8) Education level:

Education level	Dummy Variables		
	EDUCAT1	EDUCAT2	EDUCAT3
8^{th} grade or less	1	0	0
> 9^{th} grade ≤ High school	0	1	0
> High school ≤ College (Bachelor Degree)	0	0	1
> College (Bachelor Degree) ≤ Graduate Degree	0	0	0

9) Whether the household is in a flood zone:

Whether the household is in a flood zone	Dummy Variable
	FLOODZON
Yes	1
No	0

APPENDIX B

A SAMPLE OF PBS&J SOUTHWEST LOUISIANA HURRICANE EVACUATION MODEL

Terrebonne, St. Mary, Assumption and Parishes
BEHAVIORAL DATA
Southwest Louisiana Hurricane Evacuation Study 2000

Evac Zone	Participation Rates Scenario A Part. Rate Perm. Units	Scenario A Part. Rate MH Units	Scenario A Part. Rate Tour. Units	Scenario B Part. Rate Perm. Units	Scenario B Part. Rate MH Units	Scenario B Part. Rate Tour. Units	Scenario C Part. Rate Perm. Units	Scenario C Part. Rate MH Units	Scenario C Part. Rate Tour. Units	Scenario D/E Part. Rate Perm. Units	Scenario D/E Part. Rate MH Units	Scenario D/E Part. Rate Tour. Units
Terrebonne1	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Terrebonne2	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Terrebonne3	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Terrebonne4	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Terrebonne5	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Terrebonne6	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
St Mary7	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
St Mary8	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
St Mary9	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
St Mary10	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
St Mary11	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
St Mary12	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
St Mary13	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Assumption14	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Assumption15	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Assumption16	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Assumption17	1%	70%	50%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Assumption18	1%	50%	50%	2%	90%	70%	100%	100%	100%	100%	100%	100%
Assumption19	1%	50%	50%	2%	90%	70%	100%	100%	100%	100%	100%	100%
Assumption20	1%	50%	50%	2%	90%	70%	5%	100%	100%	100%	100%	100%

Scenario A Evacuation Zones

Scenario B Evacuation Zones

Scenario C Evacuation Zones

Scenario D/E Evacuation Zones

Inland Evacuation Zone (Mobile Homes Only)

VITA

Bing Mei was born on November 8, 1970, in the city of Yangzhou, Jiangsu Province, People's Republic of China. He obtained his Bachelor of Science degree in Transportation Engineering in 1992 from Southeast University, Nanjing, China. Before he joined the Louisiana State University in January 2000, he worked in the Department of Construction and Development of Jiangsu Province, China, for over five years and the Nanyang Technological University, Singapore, for two years. In August 2002, he will receive the degree of Master of Science in Civil Engineering.