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A social vulnerability-based genetic algorithm to locate-allocate transit bus stops for disaster evacuation in New Orleans, Louisiana

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A SOCIAL VULNERABILITY-BASED GENETIC ALGORITHM TO LOCATE-ALLOCATE TRANSIT BUS STOPS FOR DISASTER EVACUATION IN NEW ORLEANS, LOUISIANA

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Abstract

In the face of severe disasters, some or all of the endangered residents must be evacuated to a safe place. A portion of people, due to various reasons (e.g., no available vehicle, too old to drive), will need to take public transit buses to be evacuated. However, to optimize the operation efficiency, the location of these transit pick-up stops and the allocation of the available buses to these stops should be considered seriously by the decision-makers. In the case of a large number of alternative bus stops, it is sometimes impractical to use the exhaustive (brute-force) search to solve this kind of optimization problem because the enumeration and comparison of the effectiveness of a huge number of alternative combinations would take too much model running time.

A genetic algorithm (GA) is an efficient and robust method to solve the location/allocation problem. This thesis utilizes GA to discover accurately and efficiently the optimal combination of locations of the transit bus stop for a regional evacuation of the New Orleans metropolitan area, Louisiana.

When considering people's demand for transit buses in the face of disaster evacuation, this research assumes that residents of high social vulnerability should be evacuated with high priority and those with low social vulnerability can be put into low priority. Factor analysis, specifically principal components analysis, was used to identify the social vulnerability from multiple variables input over the study area. The social vulnerability was at the census block group level and the overall social vulnerability index was used to weight the travel time between the centroid of each census block to the nearest transit pick-up location.

The simulation results revealed that the pick-up locations obtained from this study can greatly improve the efficiency over the ones currently used by the New Orleans government. The new solution led to a 26,397.6 (total weighted travel time for the entire

system measured in hours) fitness value, which is much better than the fitness value 62,736.3 rendered from the currently used evacuation solution.

Chapter 1 Introduction

1.1 Introduction

The Intergovernmental Panel on Climate Change's (IPCC) Fourth Assessment Report (2007) indicated that increased Atlantic hurricane intensity can be expected under global warming scenarios. Southern Louisiana is one of the most hurricane vulnerable areas. There were 14 hurricanes (a new record) in the 2005 hurricane season, three of which were among the most powerful and costly in the 154-year history of record-keeping in the Atlantic Basin (Wolshon, 2006).

The best and perhaps the only way to reduce the risks when a severe hurricane approaches is to evacuate all the residents in the endangered area. Hurricane Katrina in Aug 2005 exposed the need for all levels of government officials to reassess each component of disaster preparedness, especially the mass evacuation by private vehicles and public transportation. The personal vehicle evacuation was widely considered successful by applying contraflow in New Orleans metropolitan area. Most of the residents evacuated the city before the landfall. However, over twenty-seven percent of New Orleans households had no access to private vehicles and no way to evacuate due to inadequate public transit vehicles available (Hess and Gotham, 2007). The poor, elderly, and disabled are most vulnerable. Among these non-evacuated residents, over 1,000 people lost their lives during Hurricane Katrina. The New Orleans government was therefore rigorously criticized by the public about the failure to evacuate all these residents.

To avoid the failure of evacuating the endangered residents again, the best way, accessible transit buses must move the endangered residents to shelters outside the city before hurricane landfall. However, due to the limited number of available transit buses during disaster evacuation, the government can only offer a limited number of transit bus stops. Therefore, to maximize the effectiveness of these transit bus stops, how and where to locate/allocate these transit stops poses a critical issue to the decisionmakers.

The study area in this research is the densely-populated New Orleans metropolitan area. It includes parts of the Orleans Parish, St. Bernard Parish, St. Charles Parish and Jefferson Parish (Fig.1.1). This area is bordered by Lake Pontchartrain to the north and the Gulf of Mexico to the south. There were over one million residents living in this area. The Greater New Orleans Metropolitan Area faces a big evacuation problem due to the large population and very limited road system.

New Orleans has long been considered "a disaster waiting to happen" area (Wolshon, 2006) and the disaster did happen during Hurricane Katrina. Evacuating this city is difficult because New Orleans is bounded on the north by the lake, which limits the routes out. In the last 10 years, there were already four major evacuations: 1998 for Hurricane Georges, 2004 for Hurricane Ivan, 2005 for Hurricane Katrina, and 2008 for Hurricane Gustav.

1.2 The Current Situation

In New Orleans, the City-Assisted Evacuation Plan (CAEP) is a program designed to help people who have no means of evacuating on their own due to various reasons, such as: financial need, unreliable or no transportation, or homelessness, etc. (http://www.norta.com/files/City_Assisted_Evacuation.pdf). Before and during Hurricane Katrina and Rita as well as Gustav, the CAEP was applied by the Office of Emergency Preparedness of New Orleans to evacuate the people who are willing to be evacuated during an emergency but have no accessible vehicles to self- evacuate. According to the CAEP, only those residents of Orleans Parish who meet one or more of the following criteria are eligible for help from the city: those who are homeless, those with no transportation or fuel to get out of the city, or those whose transportation mode is too small to accommodate their whole family and/or pets. In the plan, there were 17 evacuation pick-up locations, which

Figure 1.1. The study area

included four senior center locations for Orleans Parish (Figure 1.2).

During Hurricane Katrina, over ten thousand people still failed to evacuate or be evacuated before the hurricane made landfall near New Orleans. To make the transit buses convenient to for the most people in need, the CAEP cannot be deemed as a considerate plan that makes full use of the available transit bus resources. The reasons to criticize this plan are mainly twofold. First, all these transit bus stops for emergency evacuation are chosen arbitrarily by the decisionmakers almost without any criteria. The second drawback of this CAEP is that it only considers Orleans Parish. A more effective plan would take all the New Orleans Metropolitan area into consideration when locating the emergency transit bus stops, since several adjacent parishes also participated in the evacuation simultaneously.

The CAEP was changed in 2006. In preparation for the 2006 Atlantic storm season, New Orleans Mayor Ray Nagin and Terry Ebbert, director of the city's Homeland Security Department, drew upon the lessons of Hurricane Katrina and released a new evacuation plan that uses trains, airplanes, and buses to evacuate people out of town. The 2006 CAEP shows that Amtrak trains will be used to evacuate the sick and elderly, the airplanes will be held to help tourists out of New Orleans, and transit buses will be used to pick up residents with no means of transportation from designated points and deliver them to the Morial Convention Center (Figure 1.3).

Although the new CAEP shows flexibility and improves on the old plan, there are still some doubts about the effectiveness of this plan. CNN criticizes the plan because of a lack of available rail operators and doctors for Amtrak for evacuating the sick and elderly. Furthermore, agreement between the airlines and the government for evacuating tourists has not been completed. Regarding the use of buses to evacuate residents, which is the very concern of this research, CNN says that there are no more than one hundred buses available to carry over 10,000 people out of the city, and that the bus drivers have not agreed to

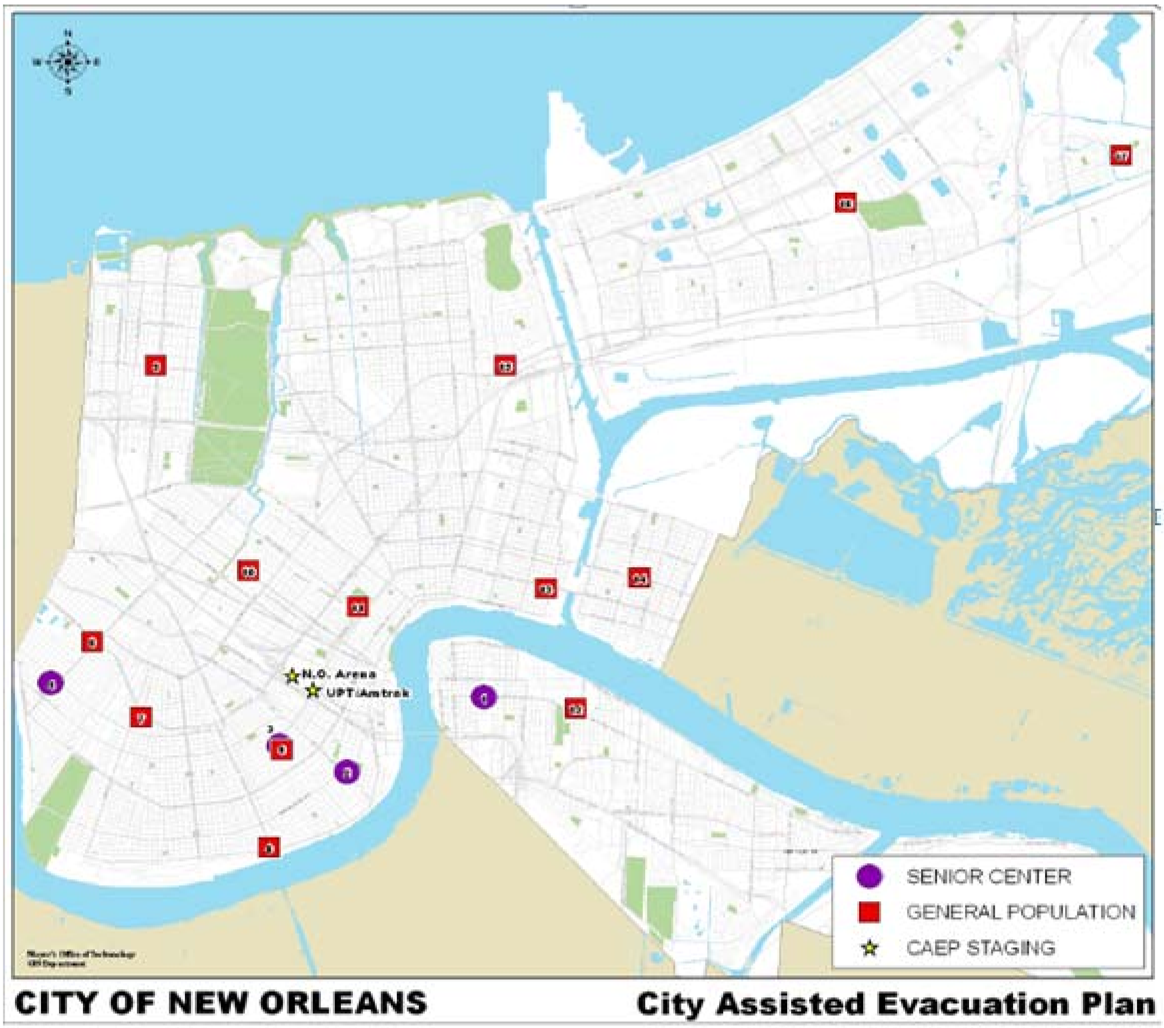


Figure 1.2. City Assisted Evacuation Plan (CAEP) of New Orleans before Hurricane Katrina.
(Source: A guide to accessing the CAEP from the office of Emergency Preparedness of New Orleans. Http://www.norta.com/files/City_Assisted_Evacuation.pdf)

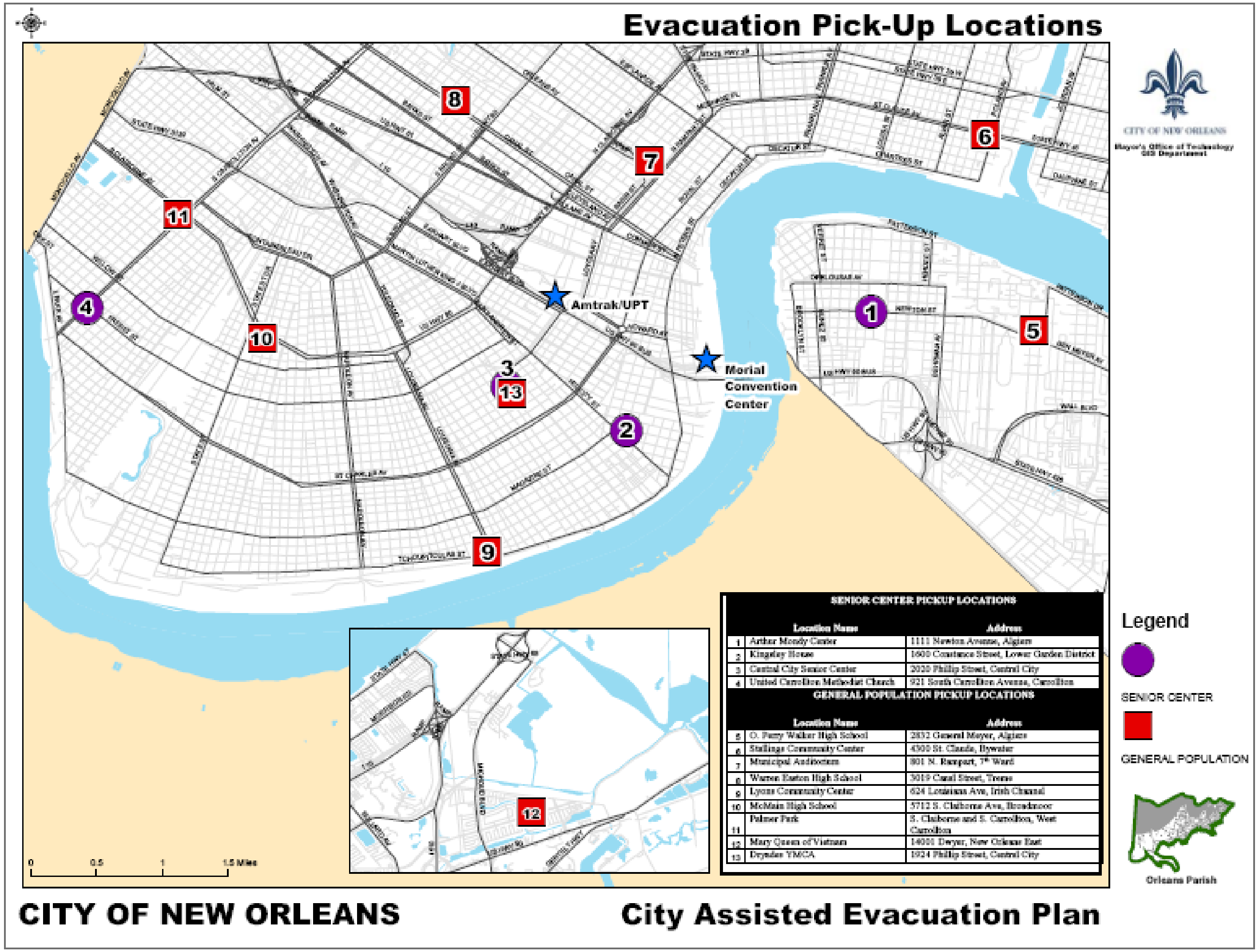


Figure 1.3. New City Assisted Evacuation Plan (CAEP) of New Orleans in 2006
(Source: City of New Orleans Mayor's Office)

remain in the city under evacuation orders

(http://www.cnn.com/2006/US/05/11/new.orleans.evacuation/index.html).

1.3 The Objectives of This Research

The objectives of this research are as follows:

1. To develop a location/allocation strategy which considers both the endangered residents' demands for convenient pick-up locations and the social vulnerability of the affected residents. In this proposed strategy, highly-vulnerable residents should be able to reach their nearest transit bus stop relatively easier in terms of the travel time. In disaster evacuation, the social vulnerability of residents should be considered because we assume that for those living in high social vulnerability areas, a relatively higher percentage of people need public transit than the percentage of people living in low social-vulnerable areas.

2. To obtain the optimal transit bus stop locations by utilizing the genetic algorithm (GA). The basic assumptions of this algorithm are that all the residents without a personal vehicle in the endangered area will be assigned a transit bus stop for evacuation, and that the overall travel time for all residents involved to reach their nearest transit bus stops should be minimized.

Chapter 2 Literature Review

This research is mainly about utilizing the genetic algorithm (GA) to locate the best bus stop locations from a large number of possible bus stops for the disaster endangered areas. “Best” in this case is defined as minimizing the total traffic demand distance from the residents’ home to the nearest pick-up locations. When deciding the locations of these transit bus stops, the different vulnerabilities of residents of the endangered locations were also identified and used. In addition, the traffic routing model was applied to calculate the minimum travel time from any resident to its nearest transit bus stop. Finally, this transit bus stop location problem is one aspect of evacuation transportation planning research, so this section will also introduce the regional evacuation problem issue.

Therefore, this chapter provides a review of five topics: disaster transportation planning research, location/allocation problem, GA, social vulnerability, and traffic routing model.

2.1 Research on Disaster Transportation Planning

The majority of previous studies on disaster transportation planning were concerned with: 1) estimating the accurate evacuation time, and 2) finding different strategies to decrease the needed evacuation time (Jamei, 1984).

Simulation models are most often used to estimate the accurate evacuation time (Chen, 2006). Due to the different level of detail in modeling traffic flow in a simulation, the simulation level can be mainly classified into two basic categories: macroscopic and microscopic. Macrosimulation is based on aggregate traffic flow. Because the implicit assumption in a flow-based model is that the flow on a link is instantaneous and homogeneous, the macrosimulation model is not so accurate. Microsimulation, the finer level, traditionally focuses on the characteristics of individual motorist and travel behavior (Hoogendoorn and Bovy, 2001). In most situations, microsimulation is the best choice as it can lead to the most accurate result (Chen, 2006). However, microsimulation requires more computing power and time to simulate.

Many studies have attempted to decrease the evacuation time needed in the endangered area by applying various strategies. The first of these types of strategies is to modify the normal road network configuration and optimize the evacuation route as well as traffic light control. Such examples include Wolshon's (2006) research on the contraflow implementation in New Orleans, which is a proven success in relieving traffic congestion during the Hurricane Katrina evacuation. Another good example is research on configuring the traffic signal to improve traffic conditions during disaster evacuation, which was conducted by Chen and Zhan (2006). In their research, approaches for signal timing to facilitate evacuation and response in the event of a no-advance-notice disaster requiring evacuation in an urban area were investigated using a simulation model constructed with data from Washington, D.C. The other kind of strategy used to decrease the evacuation time is called staged evacuation. The basic idea of the staged evacuation is to decrease the peak number of vehicles on the road at any time, thus mitigating the traffic congestion (Cova and Johnson, 2002). Chen (2006) divided the evacuation area into four parallel areas, which fall into two groups, and simulated evacuation so that the residents in different zones evacuated in a sequence. The simulation result showed that there exist some staged strategies can reduce the overall evacuation time.

The last strategy often used to optimize the evacuation efficiency is called intelligent transportation systems (ITS). The basic idea of these systems is to make timely traffic and weather information available to the evacuees, and then the evacuees can make a more suitable evacuation decision. To accomplish this, this system encompasses a broad range of wireless and wire line communication-based information and electronics technologies. technologies. When integrated into the transportation system's infrastructure, and in vehicles themselves, these technologies relieve congestion, improve safety, and enhance productivity (Urbina and Wolshon, 2003).

However, the current literature on mass evacuation plans devotes little attention to the segment of the populations who do not own vehicles (U.S. DOT, 2006; Hess and Gotham, 2007). In a "walking city" with a large number of impoverished residents, such as New Orleans, more attention to this issue is needed.

2.2 Location/Allocation Problem

Location/allocation problems are "a class of mathematical programs that seek the least cost method for simultaneously locating a set of service facilities and satisfying the demands of a given set of customers" (Sherali and Adams, 1984). Cooper (1963) built the following formulation (1) to solve this location/allocation problem:

$$x_j^{k+1} = \sum_{i=1}^{i=n} (a_{ij}\, w_{ij}\, x_{Di} /\ D_{ij}^k) / \sum_{i=1}^{i=n} (a_{ij}\, w_{ij} / D_{ij}),$$

$$y_j^{k+1} = \sum_{i=1}^{i=n} (a_{ij}\, w_{ij}\, y_{Di} /\ D_{ij}^k) / \sum_{i=1}^{i=n} (a_{ij}\, w_{ij} / D_{ij}),\ (\ j=1,2,\cdots, m) \qquad (1)$$

where:

a_{ij} is a multiplier, which is 0 or 1;

w_{ij} is the weighting factor ;

$x_{Di,} y_{Di}$ are the locations in the set of n known destinations.

D_{ij}^k is the distance between the source and the destination.

This equation is feasible for small problems. However, Cooper (1963) admitted that this method is not computationally attractive for a large number of destinations (>10). When Cooper addressed the limitation of this method, he thought that even with the modern computer's calculation capability at that time, it was still very difficult to overcome the limitation of this multi-facility locational problem. However, Cooper's research problem has been solved by using different kinds of optimization algorithms, including the GA, which was used by this research.

Facility location models are used in a wide variety of applications. These include locating warehouses within a supply chain to minimize the average time to market, locating hazardous material sites to minimize exposure to the public, and locating post offices to facilitate the accessibility of most residents, locating a coastal search and rescue station to minimize the response time to maritime accidents (Trevor and Christopher, 2003). Many other such facility location problems exist in our daily lives, even though they can be very much different in their objectives. “Minisum” and “minimax” have been the two predominant objective functions in location science (Hale and Moberg, 2003).

Location problems are generally solved on one of three basic spaces: continuous spaces (spatial), discrete spaces, and network spaces (Hale and Moberg, 2003). Continuous space means that the location problems are such that any place with x, y, z coordinates can be a feasible location for a facility. Discrete space means that the locations must be chosen from a pre-defined set of locations. Network space, which was used in this research, means that the locations are confined to the links and nodes of an underlying network.

This research aims to locate the optimal bus stop combination locations for the disaster-threatened areas, so it should fall under the realm of disaster mitigation. However, most previous disaster mitigation research dealing with the disaster location/allocation issues were concerned with locating the shelters in a region threatened by a hurricane (Sherali et al., 1991). In their research, the model selected a set of candidate shelters among a given set of admissible alternatives in a manner feasible to available resources, and prescribed an evacuation plan which minimizes the total congestion-related evacuation In the end, they concluded that the location of shelters in a region threatened by a hurricane can greatly influence the highway network clearance time, (i.e., the time needed by evacuees to escape from their origin locations to safe areas). However, Sherali et al. (1991)

did not consider the different social vulnerabilities of residents in the endangered area when locating the shelters.

2.3 The Classification of Facility Location Models

Four major general classes of location models are identified by Church (1999): median, covering, capacitated, and competitive. A median model involves locating a fixed number of facilities in such a manner that the average distance from any user to their closest facility is minimized. Covering models locate facilities to cover all or most demand within some desired service distance, such as covering the maximum population. Compared to median models, which assume that there are enough resources at each facility to handle demand, capacitated models place the limit on what can be accomplished at each facility. Competition models allow a competitor to readjust to any location decisions that other competitors have made (Church, 1999).

For this study, we consider our research problem a p-median problem because the task is to locate p facilities in a given Euclidean space which satisfy n demand points in such a way that the total sum of distances between each demand point and its nearest facility is minimized (Teitz and Bart, 1968) Specifically, this research aims to determine the optimized transit bus stop locations that can minimize the total sum of distances from the endangered residents to their nearest bus stops. The p facilities are the alternative transit bus stops, while n demand points are the census block centroids which represent the evacuees' locations.

As a P-median problem, this research question can be formulated as follows:

1. Assuming that we have 183 alternative transit bus stops, this set of 183 facilities (potential transit bus stop locations) is the set V ($|V|$=183) of all candidates to median (selected transit bus stop locations).

2. Let $VP \leq V$ ($|VP|$=20) be the set of the 20 selected transit bus stop locations. This

means that the combination of final 20 transit bus stops that will optimize the overall travel time should be chosen out of the 183 alternative bus stops.

3. When evacuation is needed, every evacuee who uses the transit bus to evacuate the endangered area will go to his/her nearest transit bus stop.

4. The goal is to select a subset $VP \leq V$ that minimizes the total sum of weighted travel time between each evacuation needed residents' home and its nearest transit bus stop (median).

2.4 Genetic Algorithm

GAs are a heuristic method used to find approximate solutions to complicated problems through application of the principles of evolutionary biology. GAs have been applied in many fields such as biogenetics, computer science, engineering, economics, chemistry, manufacturing, mathematics, and physics (Correa et al., 2004). As a heuristic method, GA can contribute to identifying the circulation eyes of tropical cyclones (TCs) (Yan et al., 2008); detecting the irregularly-shaped spatial clusters (Duczmal et al., 2007); and capturing the spatio-temporal trend in landscape pattern change of Daqing City, China (Tang et al., 2007). Because of their powerful functionality and high efficiency, they were also introduced to geography in recent years. Some geographers applied GAs to solve some traditional hard-to-resolve problems in their research.

2.4.1 Application of Genetic Algorithms in Geography

Because a huge amount of calculation and comparison is required to efficiently identify the optimal border values for separating classes, cartography is one of geography sub-disciplines that uses GA often. Armstrong et al. (2003) created multicriteria class intervals for choropleth maps by using a GA approach. In their research, they designed a piece of interactive software to find Pareto-optimal solutions for multi-objective choropleth classification problems with respect to multiple criteria instead of based on statistical ones.

Wilson et al. (2003) used a GA approach to resolve spatial conflict between objects after scaling to achieve optimal solutions within practical time constraints when making cartographic maps. GAs were also applied on restoration of gray images (Chen et al., 1999) and multi-component aerial image segmentation (Awad et al., 2007).

Huang et al. (2003) combined a GA method with GIS technology to solve route planning problems. Due to the concern for transportation security, there is an urgent need to improve the routing of trucks carrying hazardous materials (HAZMATs) on urban and suburban road networks. They evaluated the risk of HAZMAT transportation by integrating GIS and GA to set evaluation criteria for identifying and accessing the routes of HAZMAT vehicles. In their research, a GA was applied to determine the weights of the different factors in a hierarchical form, allowing for the computation of the relative total costs of the alternate routes.

Li and Yeh (2005) integrated GAs with geographical information systems (GIS) technology to study optimal location selection. Their experiments indicated that the proposed method performed much better than simulated annealing and GIS neighborhood search methods. Also, the GA method is very convenient in finding the solution with the highest utility value.

2.4.2 Applications of Genetic Algorithm on Facility-Location Problem

Because of the large number of calculations needed for a multi-facility-location problem, scientists in different disciplines such as geography (Li and Yeh, 2005), mechanical engineering (Madadi and Balaji, 2008), electrical engineering (Mendoza et al., 2007), as well as biology (Zhang et al., 2006) have already noticed the advantages of GAs and successfully used them to solve various kinds of facility location problems. The implementation of GA and GIS can effectively solve the spatial decision problems for optimally siting *n* sites of a facility.

To evaluate the optimal locations of three discrete heat sources that could be placed anywhere inside a ventilated cavity and cooled by forced convection, a micro GA was utilized by Madadi and Balaji (2008) with six coordinates of the heat sources as input parameters and five individuals composed of a population for the optimization, with the objective function as minimizing the maximum temperature of any of the heat sources. Initially for 66 generations, simulations were done repeatedly to evaluate the objective function. This data were used to train an artificial neural network (ANN) to predict the fitness from the six inputs. The result shows that by integrating ANN with GA, the computational time can be reduced substantially in location problems such as this one.

In electrical engineering, automatic voltage regulators (AVRS) help to reduce energy losses and improve the energy quality of electric utilities, compensating the voltage drops through distribution lines. To help electric companies in the decision-making process, Mendoza et al. (2007) used a GA to define the optimal locations of a set of AVRs in electric distribution networks. The result of this research showed that GA is capable of finding solutions in a very efficient way, thus giving the decision-maker a set of possible (trade-off) solutions from which to choose.

2.5 Social Vulnerability Research

Vulnerability is a term used to describe the potential for loss, which is always linked to risk, disaster, and hazard. Urban "vulnerability" refers to the inherent weakness in certain aspects of the urban environment that are susceptible to harm due to certain biological, physical, or design characteristics. It is generally defined as a measure of coping abilities of human and physical systems in the urban environment (Rashed and Weeks, 2003). There are many different definitions of vulnerability from different views with geography (Cutter, 1996). One of the most famous definitions describes vulnerability as the likelihood that an individual or group will be exposed to and adversely affected by a hazard. Social vulnerability is the interaction between the hazards of place (risk and mitigation) and the social profile of communities (Cutter, 1993).

2.6 Traffic Routing Model

A challenge of this research is how to identify the accurate distances between each evacuee and his/her nearest transit bus stop. The Euclidean distance is most often used to solve this kind of distance issue in facility location research, but in this road network study environment, it cannot represent the accurate distance. For example, if two points are located on opposite sides of a river, the Euclidean distance between them may be very small, but without an accessible bridge, the travel time between them could be much longer. In light of this, since the evacuees must travel along the road to reach the desired transit bus stops, adding the route selection model into this facility location research and then using the travel time rather than Euclidean distance can make the study results more reliable.

Due to the characters of road traffic, most of the decisions of route selection are not independent. Thus, in traffic systems the interdependence of actions leads to a high frequency of implicit co-ordination decisions (Klugl and Bazzan, 2004). Some methods already exist (e.g., radio, Internet) that can help the drivers to make decisions to find an efficient path, but most of these methods do not consider the drivers’ decision. To overcome this shortcoming, Klugl and Bazzan (2004) studied the influence of drivers' decision-making on the traffic system as a whole and how simulation can be used to understand complex traffic systems.

Empirical studies on route choice behavior have shown that drivers use numerous criteria in choosing a route, among these criteria fastest path routing has typically been adopted in-route guidance systems because of its simplicity. Through all these recent years, because enumerating all non-dominated paths is computationally too expensive, many efficient shortest path methods have been developed (Handler and Zang, 1980, Huang et al., 2007, Park et al., 2007, Santos et al., 2007). Among them, Park et al.'s (2007) method is one of the most current and accurate. The objective of their research was to develop computationally efficient algorithms for identifying a manageable subset of the non-dominated (i.e., Pareto optimal) paths for real-time in-vehicle routing. However, obtaining a stable mathematical representation of the driver's utility function is theoretically difficult and impractical, and identifying the optimal path given a nonlinear utility function is a nondeterministic polynomial time (NP)-hard problem. So they proposed a heuristic two-stage strategy that identifies multiple routes and then selects the near-optimal path in their research. The result showed that their algorithm can significantly reduce computational complexity while identifying reasonable alternative paths. Another study that dealt with shortest-path algorithm was done by Huang et al. (2007), who proposed an incremental search approach with novel heuristics based on a variation of the A* algorithm which is Lifelong Planning A* (LPA*). Huang et al. (2007) also suggested using an ellipse to prune the unnecessary nodes to be scanned to speed up the dynamic search process. Their algorithm determines the shortest-cost path between a moving object and its destination by continually adapting to the dynamic traffic conditions, while making use of the previous search results. Experimental results showed that the proposed algorithm performs significantly better than the well-known A* algorithm. In this research, we assume that each evacuee knows the best route to reach his/her nearest transit bus stop, so the shortest-path algorithm was used.

Chapter 3 Data

There are three total input layers for the GA-based facility location problem: alternative bus stops, weighted census block centroids, and major road segments. For calculation convenience, all these input layers were transformed into raster format with the same spatial resolution. This makes each image layer the same number of columns and rows of cells. The following sections describe the data used in this study.

3.1 Geographical Data

Theoretically, to find out the locations of optimal transit bus stop combination in this research is a capacitated p-median problem. One should take the total weighted distance from all residents' homes to their nearest transit bus stop into consideration and minimize this value. The census data which can represent the resident distribution normally include census blocks, census block groups, and census tracts. A census block is the smallest geographic unit used by the United States Census Bureau for tabulation of 100-percent data (data collected from all houses, rather than a sample of houses). Block groups are composed of several census blocks, and several census blocks make up census tracts. There are, on average, about 39 blocks per block group.

This research uses the centroid of each census block to represent the location of the residents living in each given census block. As a result, distance is measured from a transit bus stop to an aggregation point, which is the centroid of each census block group instead of from the dispersed residents' homes in the metropolitan New Orleans area in this research. According to Hillsman and Rhoda (1978) and Goodchild (1979), this type of data aggregation does cause errors when solving the location/allocation problems. The two reasons that it is worth the risk of the effects of data aggregation in our study are as follows:

1. We are dealing with an emergency facility problems. In terms of efficiency and accuracy,

> "When the demand is based on a highly dispersed pattern of individuals, it is necessary in the interests of manageability to aggregate to some set of more or less arbitrary statistical areas. The same is true of emergency facility problems, where a virtually continuous probability surface of demand must be collapsed onto a number of zones. The zones themselves may be chosen to coincide with standard statistical areas, such as census tracts, to allow predictive models to be built, or may be chosen to allow easy administrative implementation of the plan through the use of administrative 'building blocks'." (P245, Goodchild 1979).

2. According to Casillas's (1987) research, data aggregation only has a little effect on the patterns of locations of facilities, especially on low-level aggregated data.

Another issue in this aggregate data is that although census block data is the most accurate, we could not find some demographic data and socioeconomic data which are essential in our research when getting the different social vulnerabilities for the study areas in this census level. One feasible way to solve this problem is to calculate the social vulnerability for each census block group in the study area first, and then assign this social vulnerability value to the census block centroids falling into this given census block.

3.2 Social Vulnerability Data

The social vulnerability and population weighted census block centroid will be used to represent the evacuees who need the transit buses in an evacuation situation. Many social vulnerability indicators will be culled from the 2000 census and will be used to create a composite social vulnerability index. These data sources are indicated in Table 3.1. According to Cutter et al. (2003), major social vulnerability indicators include: lack of access to resources (including information, knowledge, and technology), limited access to political power and representation, social capital (including social networks and connections), building stock and age, frail and physically limited individuals, and type and density of infrastructure and lifelines.

The evacuees were represented by census block centroids in this research (Fig. 3.1), and the number of evacuees is the initial attribute of each census block centroid. After the

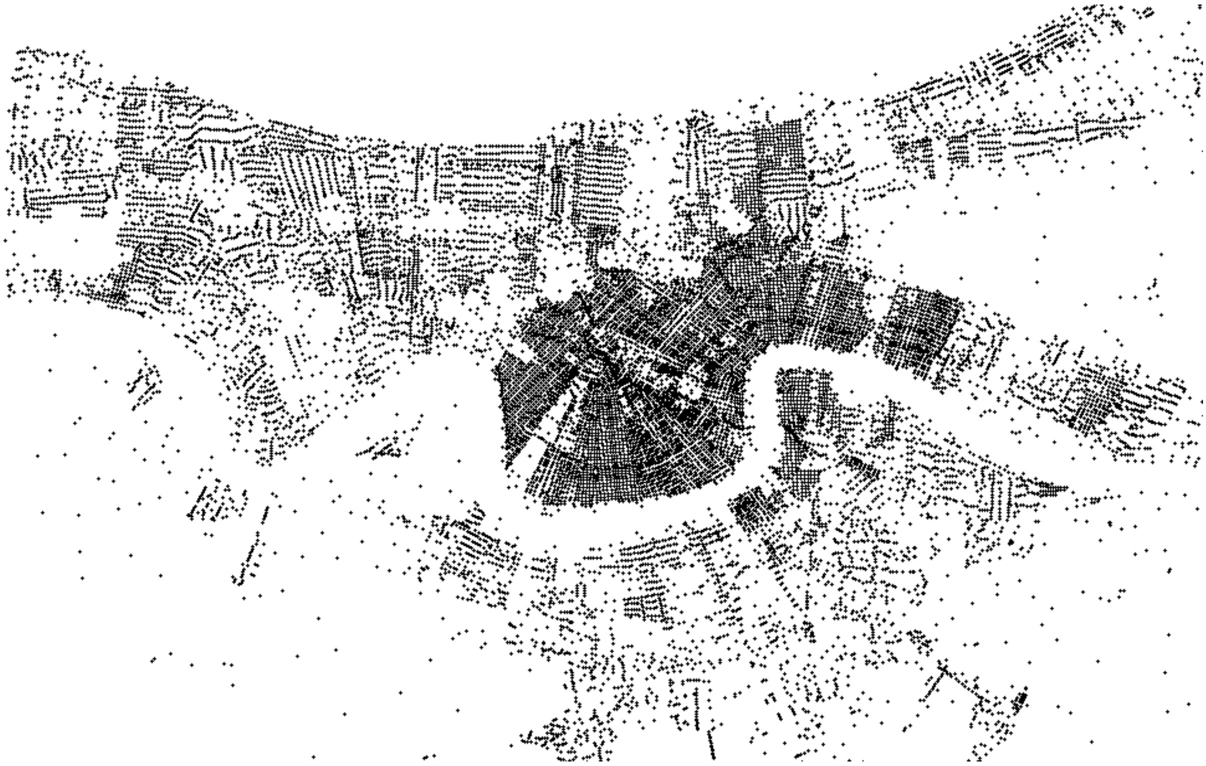


Figure 3.1. Census block centroids in New Orleans

Table 3.1. Major social vulnerability indicators used in this research (Unit: Percent)

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

social vulnerability value for each census block group in the study area was computed, the corresponding social vulnerability of the census block group in which it falls into for each census block centroid was assigned. Multiplying the value of social vulnerability by the attribute of each census block's population results in the final weighted attribute for each census block centroid used to locate the transit bus stops. The larger number of the weight of each census block will be taken more consideration when locating the pick-up locations.

3.3 Road Network Attribute

This section was co-authored with Wei Liang (see also Liang (2009)) for road network analysis.

Only the major road network was included in this GA-based facility location model, and it was digitized from Google map. The interstate highway was eliminated based on the assumption that the evacuees without accessible vehicles cannot use the interstate highway to arrive at their nearest transit bus stops. Since there are numerous detailed local road segments, it is too difficult to include them into this model. The road network map in Google has been cached for 20 levels, and from 10^{th} -20^{th} cached level, there are two kinds of yellow lines on the road map. The lighter and narrower yellow roads represent the major road network in this research (Figure 3.2), while the darker links represent the interstate highways.

The attributes for each major road segment (i.e. link) in the total driving time for all residents to their nearest transit bus stop model include: length, speed limit, start node ID, and end node ID. Start node ID and end node ID are the two end ID number of this road segment, and they were used to find the optimized route in terms of driving time. In this research, the driving time from any census block centroid to its nearest transit bus stop is the static time (i.e. by using the optimized route), which does not take into account the dynamic traffic situation.

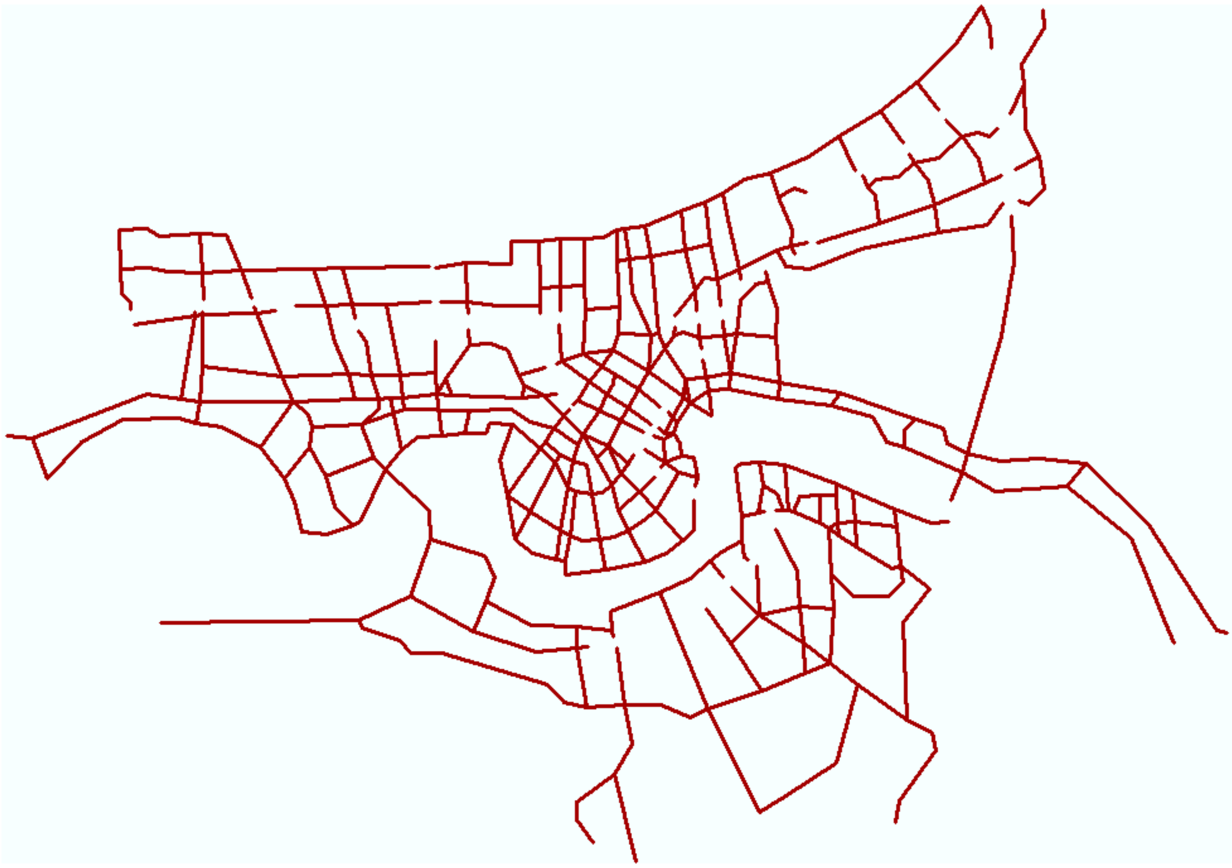


Figure 3.2. Local major road network in New Orleans

3.3.1 Nodes Attribute

Nodes are the end points (i.e. intersections) for each road segment. In the New Orleans metropolitan area, there are a total of 310 nodes for the local major road network. The attributes for each node include geographical location represented by vertical and horizontal coordinates and node IDs which are directly connected with this node by road links. At each time of iteration of one possible transit bus stop combination, the travel time of driving to all the transit bus stops will be calculated for every census block centroid, and the least one will be chosen for this given centroid as its travel time attribute.

To fulfill this nearest route selection purpose, a “shortest travel time matrix” between each pair of nodes was obtained by using Dijkstra's (1959) algorithm. Thus, the best route can always be chosen correctly by each census block centroid while they are traveling. For example, to calculate the distance between one census block centroid and one transit bus stop, the nearest nodes should be found for this given census block centroid and this given transit bus stop individually, and then the “shortest travel time matrix” should be consulted to reveal the shortest travel time between these two nodes. From this procedure, any shortest traveling time between each census block centroid and every alternative transit bus stop can be found.

3.4 Location of Alternative Transit Bus Stops

3.4.1 Criteria for Locating Alternative Transit Bus Stops

The emergency office of New Orleans did not define any criteria that should be met to be an alternative bus stop for Orleans Parish in CAEP. It simply arbitrarily chose several transit bus stops from the locations for which stops were offered. To improve the efficiency in terms of accessibility to transit bus stop locations by all evacuees who need transit buses, several rules were formulated to choose the alternative transit bus stops in this research:

1. The study area was extended from Orleans Parish only to the entire New Orleans metropolitan area.
2. “The alternative transit bus stops” are defined as the locations and facilities which can be utilized as potential transit bus stop locations. They may include all the desired schools, churches, pharmacies, recreation centers, and bus stops.
3. To be chosen as an alternative transit bus stop, a candidate must have an open area that can support seven transit buses simultaneously. The rationale of choosing seven is that there are one hundred buses available to be divided among fifteen bus stops located in Orleans Parish for evacuation preparation.

3.4.2 Decision Making in Locating Alternative Transit Bus Stops

Based on three guidelines mentioned in 3.3.1 and the fact that the CAEP plan uses high schools, community centers, churches, bus stops, senior centers, and parking lots as pick up locations, we decided to examine all the high schools, community centers, churches, bus stops, senior centers, and parking lots in the study area and selected those which meet all three guidelines as alternative transit bus stops.

Finally, 274 alternative transit bus stops which fulfilled all the criteria were selected. We input the coordinates of these alternative transit bus stops into ArcGIS software to plot their locations (Figure 3.3).

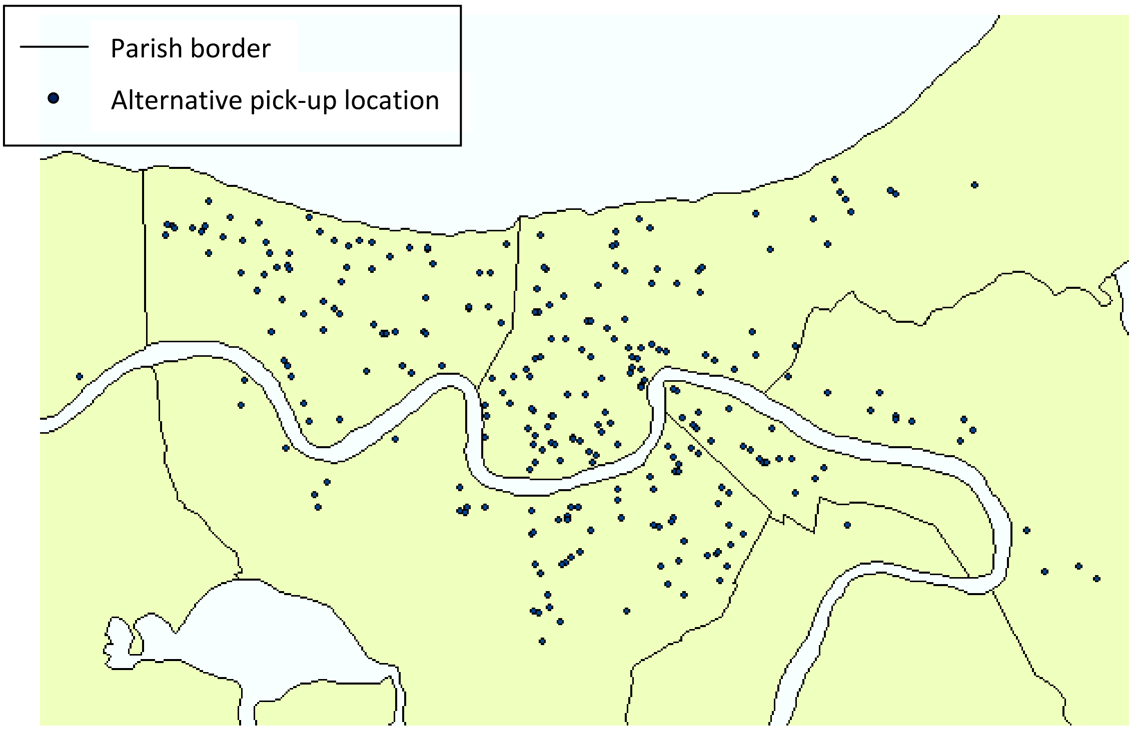


Figure 3.3. The alternative bus stop locations selected according to the criteria

Chapter 4 Methodology

Because of the advantages of genetic algorithms (GAs) on facility location problems, the social vulnerability-based genetic model developed in this research to locate the transit bus stop is expected to perform well for regional disaster evacuation. The model was programmed in MATLAB™. There are three raster input layers in this facility location model: the local major road network layer, weighted census block centroid layer, and alternative transit bus stop layer. An information layer for node (i.e. intersection) as well as other simulation parameters should also be input before model simulation. The mechanism of this transit bus stop location model is shown in Figure 4.1.

4.1 Social Vulnerability

The social vulnerability of New Orleans is not evenly distributed among different social groups and between different places. Some areas may be more susceptible to the impact of hazards than other regions based on the socioeconomic variables and demographic characteristics of residents residing within them. Similar to the purpose of the emergency office of New Orleans, the main goal of the City Assisted Evacuation Plan (CAEP) is to evacuate those New Orleans citizens who want to evacuate during an emergency, but lack the capability to self-evacuate. This segment of the population is more vulnerable than those who can access personal vehicles to schedule their own evacuation plan. In light of this, when the decisionmakers locate-allocate the transit bus stops for the evacuees willing to take transit to evacuate the endangered area, they must consider the social vulnerability of all the residents over the entire study area. This is because the higher the social vulnerability of the residents, the more likely they would use the public transit buses to evacuate in the face of severe disaster. So based on the vulnerability value, high vulnerability priority residents should have higher priority to be considered when locating the transit bus stops. This means that the decisionmakers should identify transit bus stops

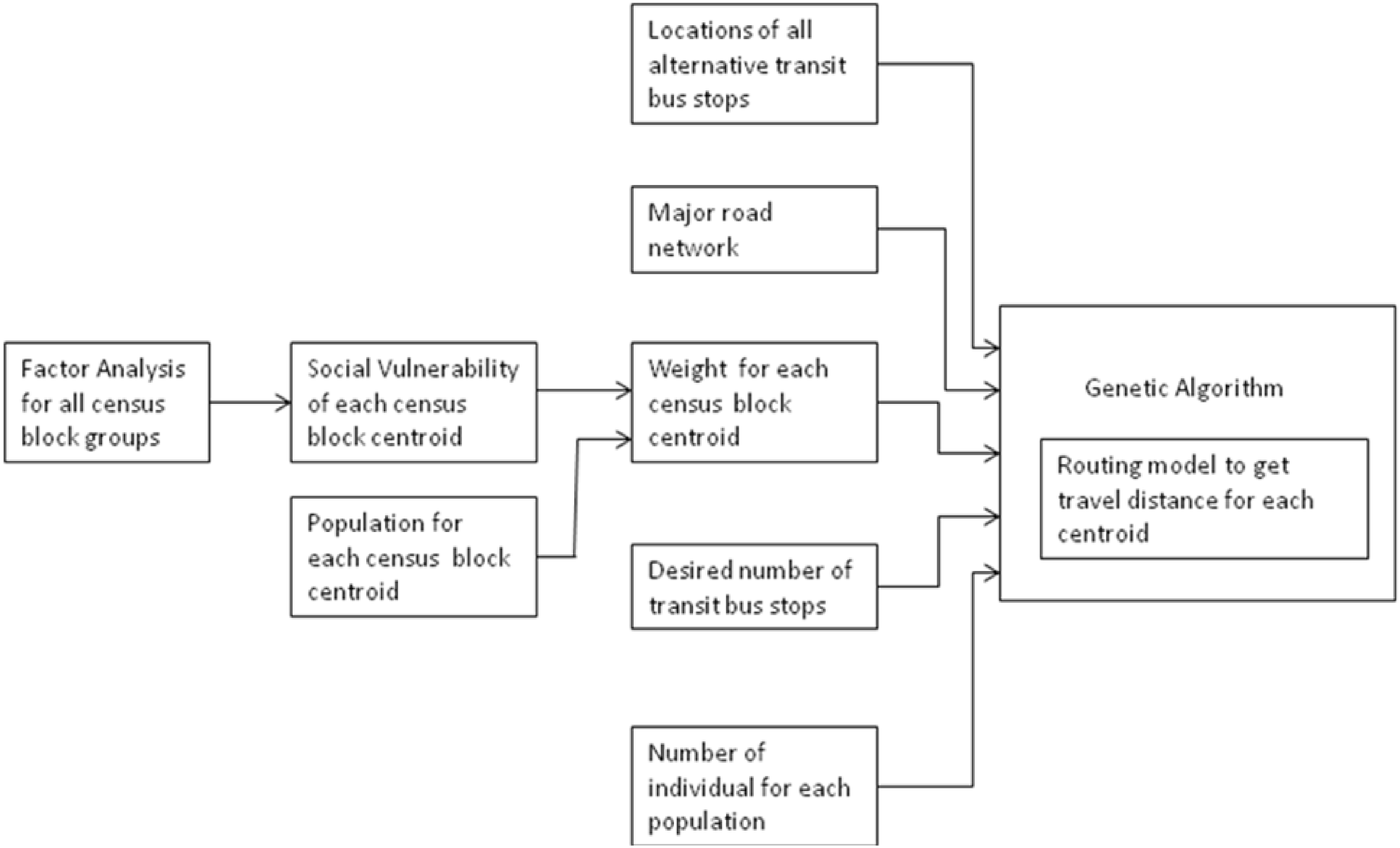


Figure 4.1. The mechanism of the transit bus stop location model

that allow for relatively easier access for those people in terms of travel time.

For the social vulnerability analysis, Cooperation with Wei Liang was undertaken (see also Liang (2009)). In this research, a modified version of Cutter's (1996) hazards-of-place model of vulnerability (Fig. 4.2) was used to examine the components of social vulnerability for the study area. Modification to the original model is as follows. In Cutter's (1996) model, physical vulnerability and social vulnerability are merged into one individual vulnerability called "place vulnerability" with an "explicit focus on locality", while in this study, the vulnerability model simply focuses on the social vulnerability. However, the decisionmakers should still keep in mind that the higher physical vulnerability area may suffer more damage from the disaster.

This modified hazards-of-place model of vulnerability was utilized to calculate the weighted distances from the centroid of each census block to their nearest transit bus stops in the New Orleans Metropolitan area.

To examine the social vulnerability, socioeconomic data were collected for all 925 census block groups, our unit of analysis, in the study area. Using the U.S. Census 2000 data, all the possible variables were collected and analyzed. Originally, more than 60 variables were collected, after all the computations and normalization of data (to percentages), 20 independent variables were used in the statistical analysis (Table 3.1). The primary statistical procedure used to reduce the data was factor analysis, specifically, principal components analysis, which is described in detail in the next section.

4.2 Factor Analysis

Because many obtained social-economic variables are inter-correlated, it is improper to integrate them together directly to obtain the social vulnerability. By utilizing factor analysis we can reduce a large number of variables to a smaller number of factors for modeling purposes, thus eliminating the inter-correlation. The technique also facilitates

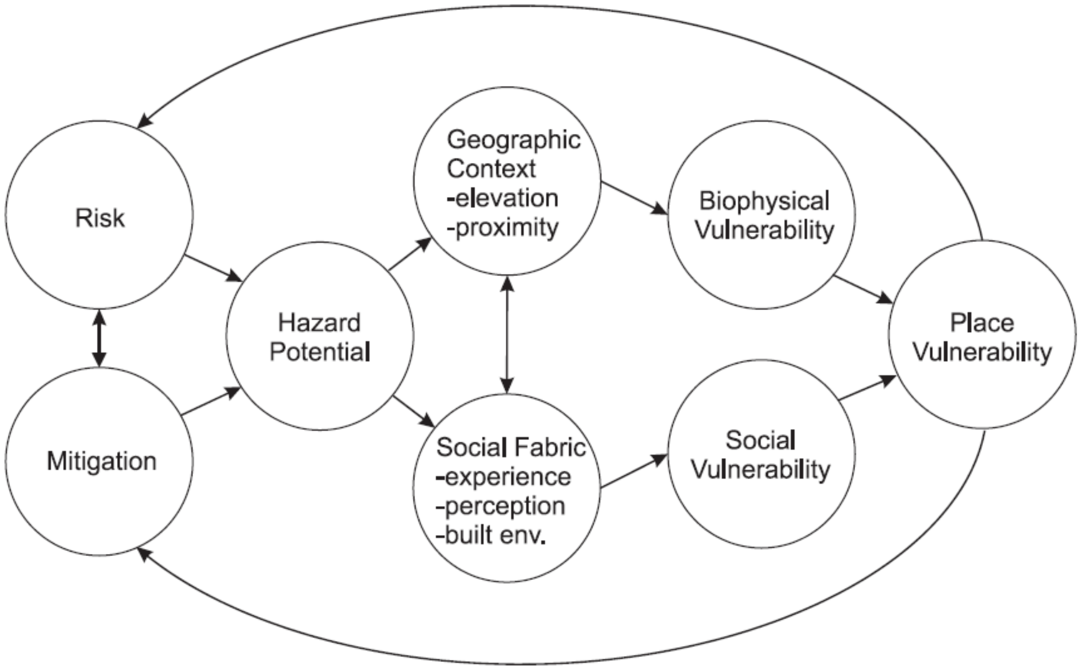


Figure 4.2. The hazards-of-place model of vulnerability (Source: Cutter, 1996)

replication of the variables at other spatial scales, thus making data compilation more efficient (Cutter et al., 2003). The first 12 factors were retained, which explained over 90 percent of the variance among all the census block groups, to differentiate the relative level of social vulnerability in 2000 in the study area (Table 4.1).

This factor analysis was performed in SPSS, and one of the important output matrices is called, "Component Score Coefficient Matrix". Each column of this matrix is a set of factor score coefficients, which were used to calculate the given factor score by using all the variable values for each of these twelve factors (Table 4.2).

After we obtained all twelve factors, a composite social vulnerability index score was produced for each census block group, and this score is a relative measure of the overall social vulnerability. Since each of these factors explains a different portion (e.g., first factor explains 32.301%, while the twelfth factor only explains 2.452%) of the information provided by the original twenty social economic variables, each factor cannot be viewed as having an equal contribution to the census block group's overall vulnerability. So, for each factor in a given census block group, its value was multiplied by the percentage of variance of the initial eigenvalue, and finally added all these twelve multiplied values together to produce the overall social vulnerability. In this calculation process, all factors with positive values indicated higher levels of vulnerability whereas the factors with the negative values decreased or lessened the overall vulnerability. For the social vulnerability result, the lowest value of all these census block groups was -1.2141, and the highest social vulnerability was 29.4907. To classify the study area into low and high social vulnerability classes, the natural break method was used to classify these census block groups into five categories (Fig. 4.3). As we can see, the most and second-most vulnerable areas were almost all located in the downtown area, while the outlying areas were relatively low in

Table 4.1. Total variance explained by each component

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

Extraction Method: Principal Component Analysis.

Table 4.2. Component score coefficient matrix

	Component													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Under5Rate	.067	-.081	-.212	.185	-.281	.328	-.283	-.260	-.098	-.360	.582	.358	.008	.413
Over75Rate	-.012	.027	.522	.079	.072	-.028	.026	-.195	-.062	.045	.064	-.091	.726	.680
FemaleRate	.062	.103	.221	.329	-.210	.358	-.262	.010	-.069	.155	-.312	-.142	-.063	-.387
DisableRat	.084	-.055	.321	.155	.081	-.193	.118	-.138	.115	.103	.486	.432	-.783	-.653
UnemployRate	.103	-.017	-.121	.017	-.040	.050	.011	.013	.365	.841	.474	-.675	.068	.104
FemaleHeadedRate	.130	.122	.086	-.009	.010	.095	-.047	-.035	-.234	-.201	-.242	-.381	-.340	.240
RentPercen	.109	.213	-.071	-.026	.120	.025	.013	-.019	-.334	-.298	.380	-.351	.365	-.423
MoreThan75000Per	-.105	.126	.058	.042	-.148	.361	-.260	.220	.212	.294	-.121	.303	.093	-.205
ServiceIndustryRate	.124	-.012	-.089	.005	-.030	-.082	.014	-.063	.170	.135	-.521	.431	.687	-.550
FamerRate	-.008	-.183	-.016	.259	.417	.021	-.334	.215	.574	-.478	-.019	-.367	.117	-.213
TransportationRate	.020	-.171	.057	.217	-.329	-.162	.276	.814	-.186	-.133	.196	-.065	.229	.057
NoEnglishRate	-.048	.252	-.160	.377	.130	-.135	.120	.057	.151	.136	-.192	.173	-.393	.815
UnMarriedRate	.128	.169	.055	-.003	.101	.049	.010	.197	-.140	-.111	-.275	-.104	-.301	.200
MinorityRate	.126	-.062	-.075	-.044	-.154	-.066	.087	.063	.169	-.038	-.470	.002	-.300	.030
ForeignBornRate	-.041	.296	-.159	.332	.055	-.177	.238	-.130	-.110	.009	.140	.049	.396	-.493
PovertyRate	.137	-.014	-.088	-.029	.054	.022	-.035	.006	.077	.053	.016	.188	.241	.314
NoHighSchool	.121	-.162	.012	.126	.087	-.130	.072	-.141	.146	.072	-.017	.419	.269	.389
MobelPercent	-.008	-.265	-.105	.155	.363	.092	-.173	.086	-.790	.456	-.135	.105	-.048	-.050
VanPercent	-.002	-.086	-.004	.014	.190	.674	.696	-.022	.128	-.089	-.017	.044	.003	-.046
HouseBefore1940Percent	.054	.241	.047	-.247	.266	.120	-.167	.530	.069	.086	.351	.537	.065	.127

Extraction Method: Principal Component Analysis.
Component Scores.

social vulnerability.

Evacuees who need to take the transit buses were assumed to know how to reach the nearest destinations (i.e. transit bus stops). This means when an evacuee arrives at a node (i.e. intersection), he/she will evaluate all the possible routes that can lead to the desired transit bus stop. After assessing these available routes, the evacuee will finally choose the shortest path in terms of the travel time. In this research, the routing sub-model, which is also called shortest path model, was used to solve this problem of how to choose the shortest path when arriving at a node.

The main purpose of this shortest path model is to find the shortest path from any origin node to all other nodes. The basic idea of this model is to build a matrix, and the shortest distance between any two nodes in the road network is stored in this matrix.

4.3 Routing Model

The basic hypothesis of the algorithm to build the shortest path matrix is contained in the equation below (Jamei, 1984):

$$d_{kj} = min(d_{ki} + d_{ij}) \qquad (2)$$

where:

d_{kj} =length of the shortest path from node k to node j

d_{ki} =length of the shortest path from node k to node i

d_{ij} =distance of i to j node.

The most famous algorithm used to find the shortest path is credited to Dijkstra (1959). His algorithm is a graph search algorithm that solves the single-source shortest path problem for a graph with non-negative edge path costs (Dijkstra, 1959). This algorithm is often used in routing, and it works by visiting nodes in the graph starting with a given node. It then repeatedly examines the closest not-yet-examined nodes, adding this node to the set of nodes already examined. It expands outward from the starting node until it reaches all the

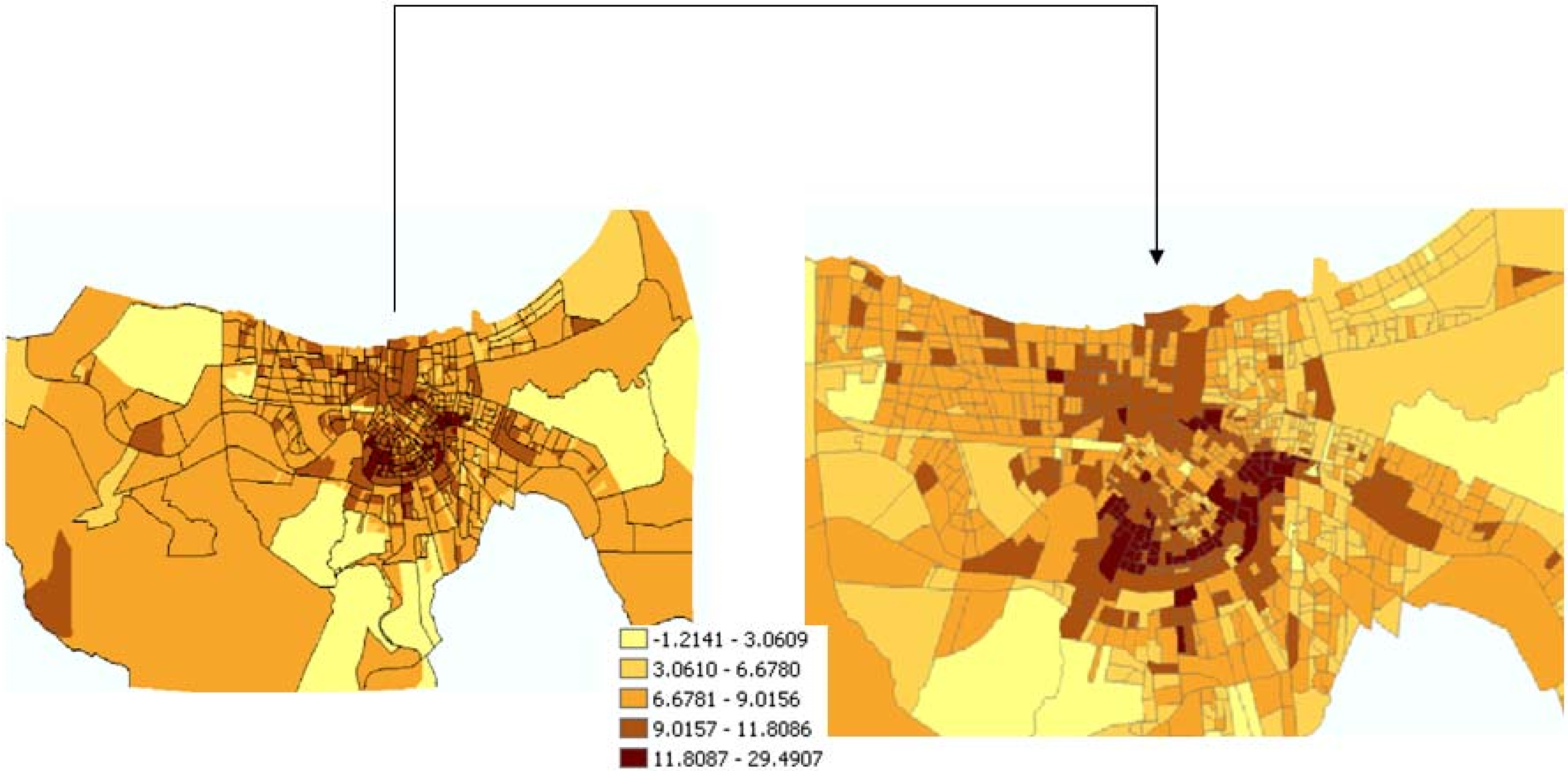


Figure 4.3. Social vulnerability of each census block group

other nodes. This above process is repeated for every node to find their shortest travel time to other nodes. And then the current travel time of all the traveled links through this routing process from the starting given node to destination node just identified should be added as the cost attribute of this beginning given node. This algorithm is applied in this research so that the optimized route to the desired transit bus stop can be found for each census block centroid.

4.4 Genetic Algorithm

The location/allocation of the transit bus stops for disaster evacuation is mainly a p-median problem, and there are several methods to solve this problem. Among them, GA is one of the most widely used and successful. GA uses techniques inspired by evolutionary biology such as crossover and mutation, and it is a heuristic algorithm used to find exact or approximate solutions to p-median problems through application of the principles of evolutionary biology to computer science (Armstrong et al., 2003; Li and Yeh, 2005).

The GA was used to solve the problem in this research because the search space is extremely large when there are a large number of alternative transit bus stop locations. It is infeasible to use the exhaustive blind (brute-force) search to solve an optimization problem that involves large amounts of spatial data. For example, the number of possible solutions to any given instance of p-median problem is shown in Equation 4.1 (Correa et al., 2004):

$$\binom{N}{P} = \frac{N!}{P!(N-P)!} \qquad (4.1)$$

where N is the number of demand points and P is the number of facilities to be located.

During Hurricanes Katrina and Gustav, there were a total of 17 evacuation pick-up sites used in New Orleans Parish (including 4 senior center locations and 13 for the general population) and two general population pick-up sites in Jefferson Parish (Fig. 4.4), and the

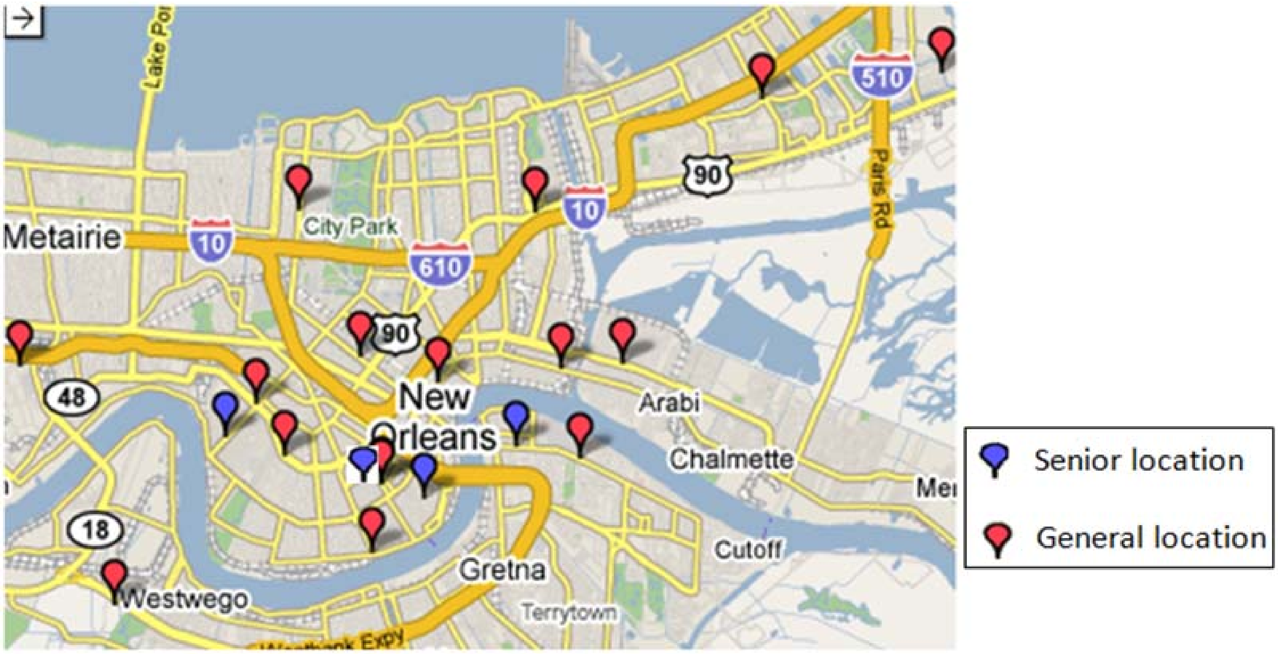


Figure 4.4. All 15 general pick-up locations and 4 senior pick-up locations
(Source: Metro New Orleans website
http://www.nola.com/hurricane/index.ssf/2008/06/interactive_hurricane_shelter.html)

state contracted for 700 charter buses for the public evacuation system. In this research, the final general population pick-up locations was set to 15 for the New Orleans metropolitan area. This number equals the number of pick-up locations for Orleans Parish and Jefferson Parish, excluding four senior center locations. Then the best locations in terms of weighted travel time for the fifteen location combination was sought by using GA.

When choosing the alternative sites in the study area, since not all the required buses should approach a given pick-up location at one time, a large open area is not required for each of these transit bus stops. Schools, churches, and convention centers that can hold at least seven buses simultaneously were chosen as alternative transit bus stops in the study area. By applying these criteria, over 200 alternative available sites were chosen in New Orleans. To identify the best bus stop combination from all these alternative bus stops, manually comparison would take too much time and may even be impossible. Therefore, the GA was explored to find the best transit bus stop combination using much less model running time. The following sections explain how to accomplish this task.

4.4.1 The Procedure of the Algorithm

Several terms about GA are defined here for this study. In the GA, a chromosome (i.e., individual) is a set of parameters which define a possible solution that the GA is trying to solve. Inside chromosomes, each bit position in the string is called a gene. Specifically, in this study, a gene is a potential pick-up bus stop, an individual is one possible solution of the 15 bus stop combination, and a population is the number of individuals in each generation (i.e. iteration). When GAs are constructed to solve the non-trivial optimization problems, several sub-operations should always be followed, i.e., encoding, initialization, fitness function, selection, crossover, and mutation. The whole procedure of GAs can be explained as follows:

Step 1 (Encoding): Choose the encoding method to enact the way to express each gene and individual.

Step 2 (Initialization): Input the required rasterized images and several model running parameters.

Step 3 (Selection): Select half of the individuals from the population as parent candidates, and group them into pairs.

Step 4 (Crossover): Apply the pre-specified crossover operator to each of the selected pairs in Step 3 to generate the child chromosomes.

Step 5 (Mutation): Apply the pre-specified mutation operator to each of the generated chromosomes with the pre-specified mutation probability.

Step 6 (Termination test): If a pre-specified stopping condition is satisfied, stop this algorithm. Otherwise, return to Step 2. The outline of GA is illustrated in Figure 4.5.

4.4.2 Encoding

Encoding of chromosomes is the first issue to be solved when dealing with the GA problem, and it depends heavily on the problem. The following encoding methods have been used with some success: binary encoding, permutation encoding, value encoding, and tree encoding. Among them, binary encoding and permutation encodings are the two methods that are most often used. Considering the characters and applying the scope of all of these encoding methods as well as the research question itself, the permutation method is found to be the most suitable one to be used in this research. This is mainly because the permutation encoding is useful for ordering problems, and every chromosome is a string of numbers that represents a position in a sequence in this method. In this research, every gene in a chromosome should represent an alternative transit bus stop ID. Figure 4.6 is a sample chromosome in this research.

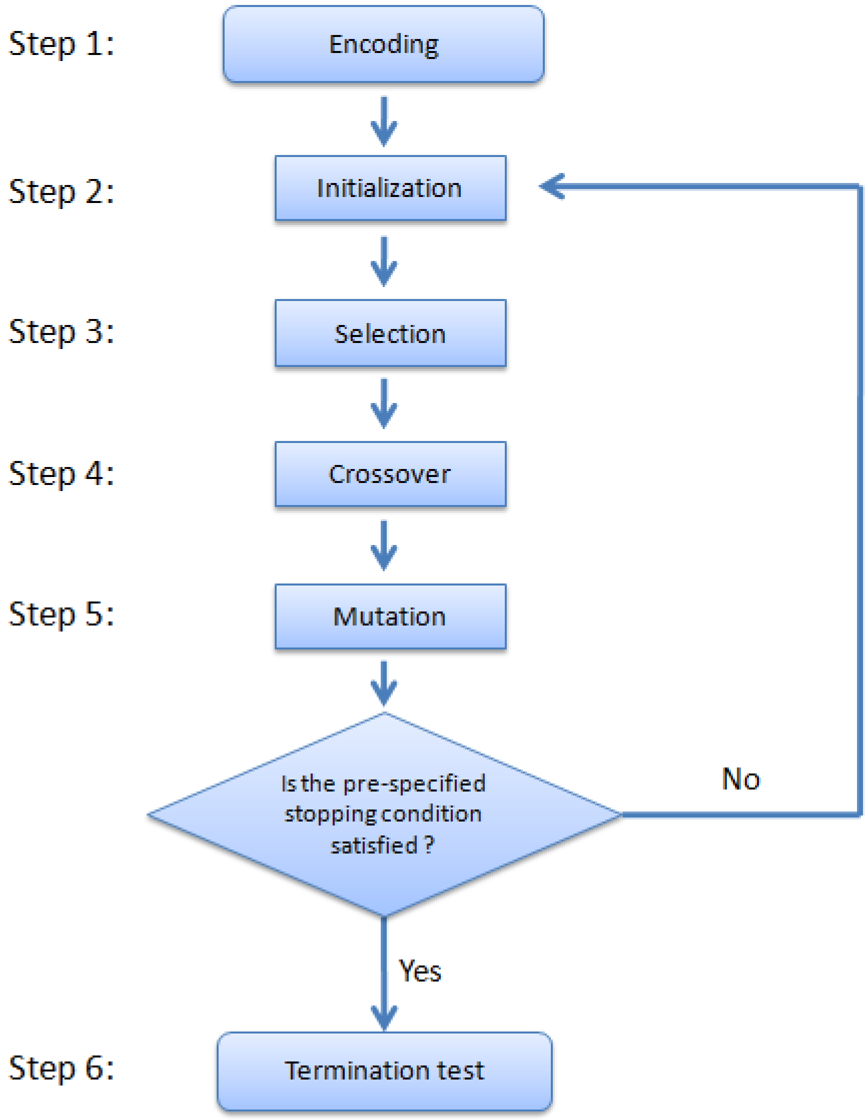


Figure 4.5. The genetic algorithm procedure

35	133	13	79	242	54	8	182	117	219	72	90	42	21	197

Figure 4.6. A sample chromosome

4.4.3 Initialization

To process the GA model in MatLab, four rasterized images should be set as input with the same spatial range and resolution. These four layers are: the census block centroids with population attribute; census block group with social vulnerability; alternative transit bus stops; and the major road network with speed limit attribute for each road segment.

Besides these input rasterized images, both the number of individuals (i. e., chromosomes) in each generation population and the desired number of transit bus stops should be specified in the program before running the model. So, at the initial phase of the model running period, n individual solutions are generated to form an initial population. In a population, each individual is a possible transit bus stop combination solution which contains 15 alternative pick-up location IDs (i. e., genes) in this research. And all the IDs of pick-up locations in any of these initial individuals are generated randomly. Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

4.4.4 Selection

To generate new children chromosomes in the GA, selection is the first operation which selects two parent chromosomes form the current generation. In each generation, this selection process is repeated several times until half of the chromosomes have been picked out as parents, and no chromosome has been selected twice in this generation.

There are mainly two ways to do the selection: the roulette wheel selection scheme and the rank-based selection scheme. The roulette wheel selection is also called stochastic sampling with replacement, which is the simplest selection scheme. Its technique is similar to a roulette wheel with each slice proportional in size to the fitness. On the contrary, by using the rank-based selection, which is used in this research, the population is sorted according to the fitness value. The one which has the highest fitness value will be ranked as the first chromosome in the current generation of population. This fitness value is calculated by using the fitness function, which is a particular type of objective function that quantifies the optimality of a individual (i. e., a chromosome) in a GA so that the particular chromosome may be ranked against all the other chromosomes. For each individual, the fitness function in this research is to calculate the total weighted travel time for all the census block centroids to their nearest pick-up locations. The weighted travel time for each census block centroid is obtained by using the following formula:

Weighted travel time=$a * b * c$; (4.2)

Where a is the shortest travel time from the given census block centroid to its nearest pick-up location, and the unit is hour; b is the population of this census block; and c is the social vulnerability of this census block.

So, in this selection process, parent chromosomes are selected by weight and are chosen randomly from the current population. A chromosome with a high fitness value has more chance to be selected as a parent than a chromosome with a relatively low fitness value, and the weight is the fitness value.

4.4.5 Crossover

Crossover is an operator to generate next generation child chromosomes from parent chromosomes. Various crossover operators have been proposed for GAs. The crossover operators for permutation chromosomes are different from those for binary chromosomes because permutation problems usually have a requirement that each element of a chromosome should appear only once in the chromosome.

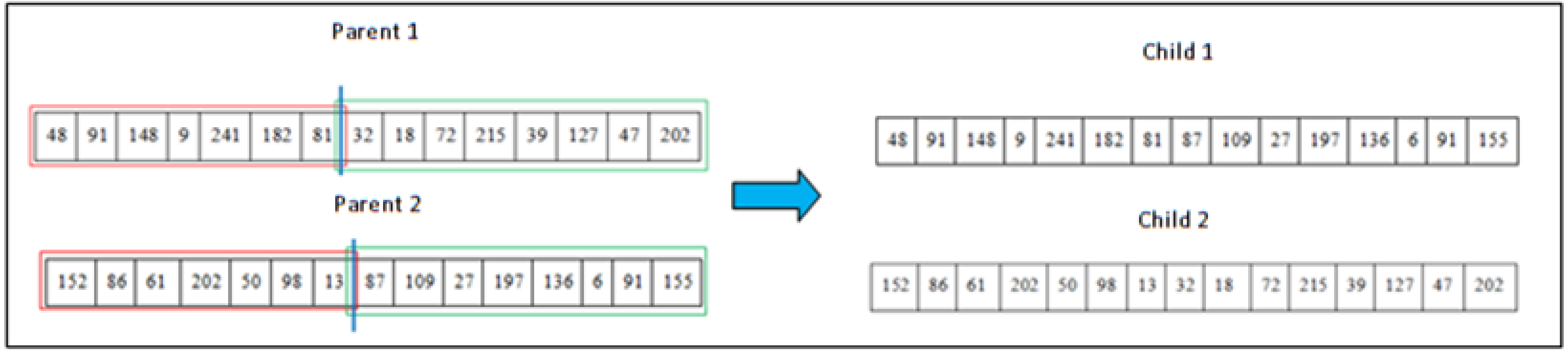
The standard one-point crossover is the typical operator for permutation chromosomes. The operator is applied to selected parent chromosomes as follows: a pre-defined crossover point is selected between two adjacent elements. Two new chromosomes are generated by swapping all elements in the head part of the chromosomes. Since two parents produce two children, and only half of the individuals are being selected as parents from each generation population through one selection operation, we should do the selection twice to guarantee that the number of individuals in each generation's population is the same.

When crossover occurs for the parent individuals, we try to cut both of them in the middle and then swap. Because each chromosome contains 15 genes in this study, for each pair of the parents from the first time selection, all the genes from the first position to the seventh position are swapped (Fig 4.7 (a)). Likewise, for each pair of the parents from the second time selection, all the genes from the first position to the eighth position are swapped (Fig 4.7(b)). In this way, two new children are generated.

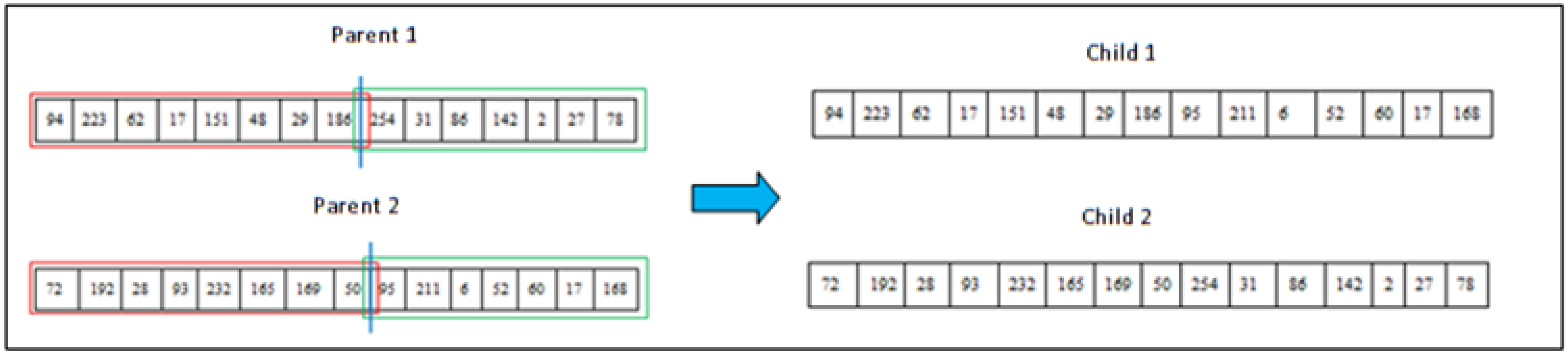
4.4.6 Mutation

Mutation is a genetic operator to alter elements in a chromosome which is generated by a crossover operator. The common method to implement the mutation operator is to generate a random variable (gene) from the gene pool which is obtained in the initiation step for each chromosome. The purpose of mutation in GAs is to avoid "local minima" by preventing the population of chromosomes from becoming too similar to each other which will result in prematurity of evolution or even stop evolution. Applying mutation in GAs is very critical because this is the essential way to maintain the genetic diversity.

In this study, 2 percent of the total genes are mutated in each generation population (the number should be $15*n$, where n is the number of individuals in each population). By doing this, all the genes are checked in each individual in that crossover, as former steps may create the same genes in one single individual, which is prohibited. All of these duplicated genes are mutated and assured to be unique in its individual after mutation. If all the numbers of these duplicated genes is less than 10 percent of the total genes in each generation, the rest of the genes from any individual are randomly chosen for mutation to compensate this demand number.



(a)



(b)

Figure 4.7. An example of two crossover methods used in this research

4.5 Results

Before the model is run, the number of individuals in each population must be set. It is easy to understand that the more individuals in a population, the better chance we can obtain the best solution from the model simulation result. However, as the number of individuals increases in each population, the GA model running time will be increased correspondingly. This makes the model running time and running result reliability a tradeoff relationship. To solve this issue, the GA model was simulated with different parameter settings (i.e. number of individuals in each population) many times, and the identification of the most suitable one was done (i.e. with the least number of individuals that can find the correct result). Within one single simulation, the indicator to check the effectiveness of each setting is the mean fitness value. Then the optimized solution is assumed to be found (i.e. simulation could stop) when the mean fitness value change is less than 0.1 percent for 10 consecutive generations. The model was run on a workstation with a dual core 2.41 GHz CPU and 8 GB memory. Table 4.3 shows the results of the recorded average final best fitness value from running the model 10 times with the same setting.

From Table 4.3 we can observe that the final best fitness value becomes almost steady (i.e. within 1% change) after the number of individuals exceeds 160. So the conclusion is that any number of individuals more than 160 in a population can obtain an acceptable pick-up location combination. And finally 200 is chosen as the number of individuals for each population in this research.

By using the setting of 200 individuals for one population, the GA model is run 10 times. Results suggest the best final combination (Figure 4.8) with its best fitness value is 26397592. The mean and best fitness values of each iteration for model simulation are shown in Figure 4.9. The names of the final pick-up locations and the percentage of the buses which should be assigned to these final pick-up locations are listed in Table 4.4.

Table 4.3. Final best fitness value with different number of individual in each population

Number of individuals in each population	Final best Fitness value (unit: weighted hour)	Model running time (unit: hour)
40	28,178.1	1.2
80	27,351.1	2
120	26,713.2	3.1
160	26,526.5	4.2
200	26,452.2	5.4
240	26,419.7	6.8

Figure 4.8. The 15 pick-up locations derived from the genetic algorithm.

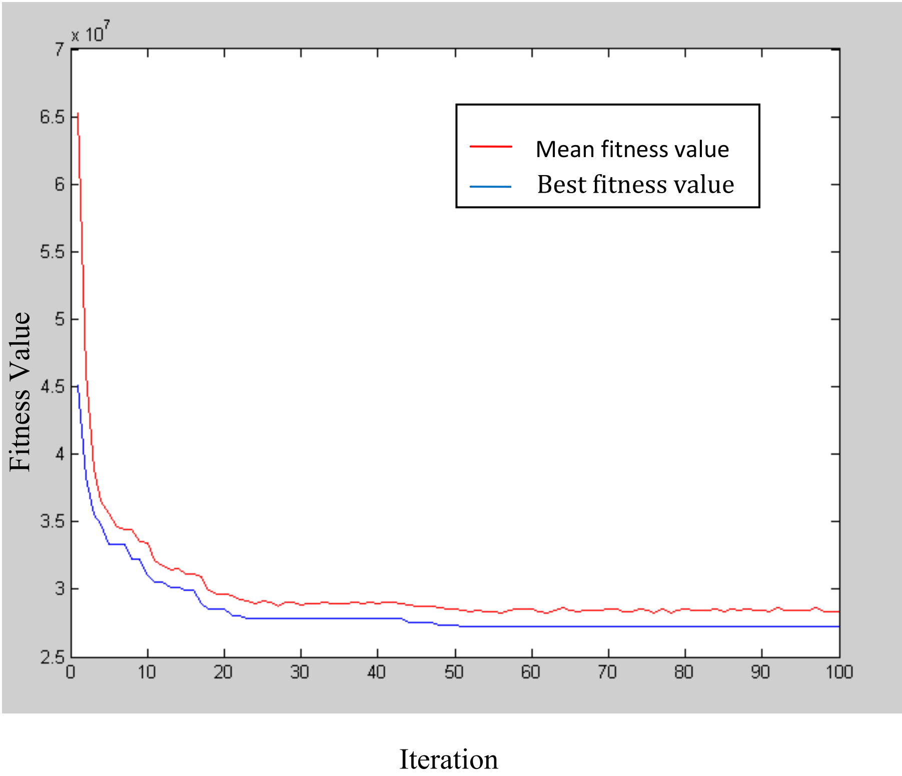


Figure 4.9. The mean and best fitness values for each iteration.

Table 4.4. The final pick-up locations and their bus quotas

ID	Name	Bus quota	Parish
1	Archbishop Shaw High School	8.2102%	Jefferson
2	Fisher Middle/High School	5.5492%	Jefferson
3	Walgreen's	5.6633%	Orleans
4	Laurel Elementary School	5.0867%	Orleans
5	Walgreen's	2.6816%	St. Bernard
6	Shops at Canal Place Parking Lot	7.4045%	Orleans
7	A. C. Alexander Elementary School	2.0444%	Jefferson
8	Rite Aid	3.6142%	Orleans
9	St. Marys Dominican High School	15.5014%	Orleans
10	Lucille Cherbonnier Elementary School	5.5543%	Jefferson
11	Gretna Middle School	19.1699%	Jefferson
12	Lusher Charter School	11.4306%	Orleans
13	Sanchez Center	5.2202%	Orleans
14	Rite Aid	1.4442%	Jefferson
15	J. B. Martin Middle School	1.4252%	St. Charles

To examine the effectiveness of these pick-up locations, the 15 pick-up locations used for Hurricane Gustav evacuation by New Orleans Government and Jefferson Parish government were input into the same simulation environment. The overall vulnerability weighted travel time was calculated for it. The fitness value was 62,736.3, which is much larger than the fitness value of the pick-up location combination identified in this research. So the conclusion can be drawn that the pick-up location combination obtained from this study can greatly improve the efficiency in evacuating the residents who need public transit in the New Orleans metropolitan area.

Chapter 5 Conclusions

5.1 Conclusions

When a disaster threatens a regional area, the best way to evacuate residents without accessible vehicles is by using transit buses. However, since the residents who need the buses to evacuate are spread throughout the endangered area, the location of these pick-up locations must minimize the overall weighted travel time for all the evacuees in need, and allocation of the available buses to these bus stops should be seriously considered by decisionmakers. This study aimed at solving this tough problem by incorporating three new aspects: social vulnerability, network analysis, and genetic algorithm (GA).

1) When deciding where to locate these pick-up locations, the first aspect we took into consideration is the social vulnerability in the study area. We assumed that a higher percentage of residents living in the high social-vulnerability area would use the transit buses to evacuate than people living in low social-vulnerability areas.

Based on the method in Cutter et al.'s (2003) study, we obtained about 20 social-economic variables, and then used factor analysis to eliminate the inter-correlation among all the variables. Among obtained 20 factors, the first 12 factors were used to calculate the final social vulnerability for each census block group. The vulnerability values ranged from -1.2141 to 29.4907.

2) The road network travel time has also been utilized to calculate the distance between each census block centroid and its nearest pick-up location. The accuracy of this method should be much better than the simple Euclidean distance. To compute the travel time between two points, the major road network in New Orleans was used in this research.

All three variables, shortest travel time for each census block centroid, its and social vulnerability, were multiplied and used are to compute the final weighted travel time for each given census block centroid. The total weighted travel time for all census block centroids is the fitness value for each bus stop combination.

3) There are 274 alternative locations that fit the criteria as the pick-up locations, and 15 of them are selected as the optimal bus stop locations. Through the use of GAs, the best combination was identified. By comparing the total travel time, the new solution led to a fitness value of 26,397.6 (weighted hours), whereas the old solution which used 15 pick-up locations by the New Orleans government results in a fitness value of 62,736.3 (weighted hours).

The results from this study show that the current pick-up locations used by the New Orleans government are not located wisely in terms of the total weighted travel time for all the evacuees, while the pick-up location combination obtained from GA offers a dramatic improvement over the current one.

5.2 Future Research

The limitation of this study is that it used Cutter et al.'s (2003) method to obtain social vulnerability by calculating 20 social-economic variables. Future research is needed to find better ways to quantify the social vulnerability.

Another aspect that can improve the accuracy of the result is to use more complex road networks. In this study, we only considered the major road network in New Orleans when calculating the minimum travel time between two points. If we can add the local roads and all highways into this routing model, the accuracy of the results can certainly be improved.

The methods used to select the best pick-up location combinations in this research can be extended to other research questions, such as in locating the distribution stations for temporary food supply to the refugees after the disaster.

Finally, in location/allocation literature, different criteria can be used. Instead of minimizing the total travel time, a different criterion could be to minimize the maximum travel time. Future research could explore the different optimization functions.

This research also need for good data. If we have data on the people who will use the bus and their locations, the results will be more accurate and useful.

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Vita

Xiaojun Qin was born to Meiyun Wang and Hongping Qin in Anhui, China, in October, 1979. Growing up in a frequently flooded area, she has the childhood memory of fighting the flood and evacuation. She attained Beijing Normal University, China, where she obtained a Bachelor of Arts degree with a major in Chinese language and literature in 2001 and a Master of Arts degree in Chinese language and characters in 2004. After graduation, she worked in China Land and Resources News Agency as a journalist and editor for one year.

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