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Optimizing the Use of Public Transit System in No-Notice Evacuations in Urban Areas

Fatemeh Sayyady

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OPTIMIZING THE USE OF PUBLIC TRANSIT SYSTEM IN NO-NOTICE
EVACUATIONS IN URBAN AREAS

By

Fatemeh Sayyady

A Thesis
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
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Mississippi State, Mississippi

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OPTIMIZING THE USE OF PUBLIC TRANSIT SYSTEM IN NO-NOTICE
EVACUATIONS IN URBAN AREAS

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Natural or man-made disasters result in unfortunate events around the nation every year. Such extreme events necessitate the short-notice or no-notice evacuation of a large population from the stricken area. This research presents an optimization modeling technique to develop an evacuation plan for transit-dependent residents during no-notice disaster situation. The proposed plan relies on the application of existing public transit system of an urban area. The public transit routing plan (PTRP) problem is formulated as a mixed integer linear program. The PTRP identifies the optimal routes for transit vehicles to move evacuees from the danger zone to designated safe destinations. A heuristic TABU search algorithm is used to find high-quality solution in a reasonable amount of time. Finally, DYNASMART-P is used to evaluate the effectiveness of the developed PTRP. Numerical experiments are conducted using the traffic network of the city of Fort Worth, TX, to illustrate the proposed modeling technique.

DEDICATION

To my beloved family ...

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CHAPTER I

INTRODUCTION

Natural disasters (such as hurricanes, floods, earthquakes, etc.) or man-made disasters (such as nuclear power plant explosions, chemical spills, terrorist attacks, etc.) result in unfortunate events every year. Such extreme events necessitate the short-notice or no-notice evacuation of a large population from the stricken area. In this context, no-notice evacuation is called when any unexpected incident occurs. No-notice evacuation is different from short-notice evacuation with prior notice, which comes from weather forecasting technologies or landfall prediction models. This research presents an optimization modeling technique to develop an evacuation plan for transit-dependent residents during no-notice disaster situation. The proposed plan relies on the application of existing public transit system of an urban area.

Public transit is an extremely versatile and flexible mode of transportation that can provide services to a great number of people in emergency situations. Following the attack on the World Trade Center in 2001, the timely decision made by the transit operators resulted in safe evacuation of hundreds of thousands of people from lower Manhattan. In Washington D.C., the clog in traffic network made public transit the only transportation mode to evacuate citizens from Washington and northern Virginia. The

successful application of transit in September, 11 highlighted the critical role of the transit system in emergency situations.

By the increasing number of destructive incidents such as terrorist attacks the researchers and practitioners have given more attention to no-notice evacuation. The conducted researches, though increasing gradually, are sporadic and limited to the specific facets of the evacuation practice. To the authors' best knowledge, analytical approaches that model the application of the public transit does not exist in literature and practice.

In this research we investigate how the public transit system can be utilized to evacuate transit-dependent citizens in no-notice incidents. The main contribution of this paper is that it proposes a network flow-based methodology to find the optimal public transit routing plan unique to no-notice evacuation. The problem itself, and also the proposed modeling methodology, is the first time practice published in the no-notice evacuation research literature.

The proposed methodology is comprised of 2 stages: optimization and simulation. In the optimization stage, a mixed integer linear programming formulation is used to model the routing of the public transit system. The proposed public transit routing plan (PTRP) identifies the optimal routes that transit vehicles follow in order to move the evacuees from the danger zone to the designated safe destinations. The elapsed time to find the solution is an important concern in no-notice incidents. Thus, the long running time of the exact solution approaches motivates the application of the heuristic TABU search algorithm to find comparable solutions in a considerably shorter amount of time. The performance of the TABU search algorithm is compared with CPLEX.

In simulation stage, we use a dynamic network analysis and evaluation tool, DYNASMART-P to evaluate the effectiveness of the developed public transit routing plan. DYNASMART-P is classified as a mesoscopic traffic analysis tool. The unique application of DYNASMART-P is used to support our research project, which involves the utilization of transit vehicles to evacuate people in emergency situations.

CHAPTER II

EMERGENCY EVACUATION

1. Introduction

Natural disasters (such as fires, hurricanes, tornadoes, flash floods, tsunamis, earthquakes, etc.) or man-made disasters (such as nuclear power plant explosions, chemical plant explosions, hazmat releases, dirty bomb threats, etc.) affect millions of people every year. Evacuation is an emergency management strategy used to ensure a population's safety in these types of situations. *Emergency evacuation is defined as the relocation of a threatened population to a safer area due to an immediate or predictable life-threatening danger* [25]. Prior to 1979, the models developed for evacuating people and vehicles from dangerous locations were mainly qualitative. However, the accident at the Three Mile Island nuclear power plant near Middletown, Pennsylvania, in 1979 provided a major motive for quantifying emergency response plans [36]. Since then, a number of optimization- and simulation-based models have been developed to identify evacuation strategies for communities (urban and rural areas), buildings and industrial plants, and residential areas. The most recent and challenging developments in this area are real-time traffic management and agent-based models.

2. Applications

2.1. Community Evacuation

Southworth [35] models a community evacuation plan using a five-step procedure that involves trip generation, trip departure time, trip destination, trip route selection, and evacuation plan set-up and analysis. The factors that affect any of these steps are the distribution of the population that is at risk, human behavior, transportation infrastructure, road capacity, vehicle utilization, accessibility of warning technologies, time available before the occurrence of the hazard, evacuees' route and destination selection, promptness in cleaning and preparing to operate the affected highways and roads, traffic management actions and the availability of non-evacuation based protective actions, such as in site sheltering [6, 7, 9, 35, 36]. The next sections of this article provide a summary of the research related to the above mentioned steps.

2.1.1. Community Evacuation: Trip Generation

The trip generation step determines the number of vehicles loaded to the traffic network during the evacuation. The number of vehicles loaded in the network depends on the population of the evacuation zone (which is space and time dependent), number of vehicles per household and vehicle utilization rate. The population of an evacuation area consists of the *permanent residents*, the *transients* (tourists and daily workers), and the *residents of special facilities* such as students, prisoners, patients, customers in shopping malls, and members at recreational facilities [35, 36]. For a given residential area with a

population size equal to N , Southworth [35] estimates the daytime population using the following equation:

$$D = H + W + P + S \quad (1)$$

where W , P , and S denote the number of workers, students, and residents of special facilities, respectively. H denotes the number of people who stay at home during the day and is estimated by:

$$H = [N - (W + P)] * (1 - s) \quad (2)$$

where s is the probability that a non-working adult (or a child) is not being engaged in shopping, recreational or social activities. Based on Southworth [35], the vehicle utilization rate depends on the time of the evacuation, the household size, the average number of commuters per vehicle and the average number of workers and licensed drivers per household. Estimating vehicle utilization rate is challenging. This is why some post evacuation surveys report significantly different utilization rates. For example, Baker [1] estimates the vehicle utilization rate to be 52 percent and Lindell and Perry [23] 75 percent.

2.1.2. Community Evacuation: Trip Departure Time

This is the time it takes one to evacuate once the evacuation warning is released. The trip departure time consists of the time required to receive the official evacuation warning, the time required to leave the current location to get home, the time required to arrive home, and the time to prepare to leave home. Next, we give a summary of the approaches used to calculate trip departure time.

In 1984, Jamei [18] introduced the *mobilization curve* to estimate the percent of evacuees that enter the traffic network in specific time intervals. The mobilization curve is represented using the following equation:

$$P_t = 1/(1 + \exp[-z(t - h)]) \quad (3)$$

where P_t is the cumulative percentage of traffic volume loaded in the network by time t , z is the response rate of the public to the disaster and is known as the slope of the mobilization curve, and h is the “half loading time”. The loading time depends on the incident and its relative severity. Radwan *et al.* [29] and Hobeika and Kim [17] have incorporated the mobilization curve in mass evacuation computer programs (MASSVAC 3.0 and MASSVAC 4.0) to determine the loading rate of evacuees. This approach relies on the planner's judgment in calibrating the model parameters z and h .

In 2000, Urbanik [36] developed a *probability distribution* of the trip departure time. He defined the probability distribution of an activity time based on the percentage of the population that completed the activity within a given time span. To simplify, he assumed that the probability distribution of trip departure sub-activity times were

independent. Then, he derived the probability distributions of trip departure time as the joint probability distribution of sub-activities involved.

None of the above mentioned approaches consider the impact of human behavior on trip departure time. The work by Murray *et al.* [27, 28] addresses the tendency of households to gather and then evacuate as a single unit. They believe that this type of behavior increases the departure time and, as a consequence, the evacuation time. Their evacuation model is based on a network flow formulation of the problem. In this network, the nodes represent residential and other possible meeting locations. The arcs represent the shortest path between nodes. Two linear integer programming formulations of the problem are given that consider a realistic presentation of human behavior in emergency situations. The first formulation determines the household meeting location while minimizing the maximum travel time of family members. The second formulation determines the route assignment along with the non-drivers' pickup schedule by minimizing the linear trade off between waiting time and travel time. For a more extensive review of the impact of human behavior in trip departure time, see [20, 24, 33, 40].

2.1.3. Community Evacuation: Trip Destination Selection

In emergency situations, the most straight- forward approach that evacuees follow in choosing a destination is the shortest evacuation plan (SEP) [38]. Based on SEP, the evacuees seek the closest exit that channels them away from the danger area. In 1996, Yamada [38] presented an emergency evacuation plan for a city using two network flow

optimization models. In these models, the residential areas (RA) and places of refuge (PR) are the nodes of the network, and the roads between them are the arcs. Yamada assumes that the roads are bi-directional with the same travel time in both directions and that the evacuees traverse roads on foot at a uniform speed. He introduces a dummy node, v^+ . v^+ is then connected to each RA node. The new network is denoted by $G^+ = (V^+, E^+)$ and $V^+ = V \cup \{v^+\}$, $E^+ = E \cup \{(v^+, d) \mid d \in D\}$. V is the original set of nodes (RA and PR nodes), E is the original set of arcs and D is the set of RA nodes only.

The first model does not consider node and arc capacities. The model minimizes the individual and total travel distance. Yamada applied the Dijkstra algorithm with v^+ as the source node and PR as the demand nodes. This algorithm runs in $O(|V^+|^2)$. The optimal solution for this network flow problem is a forest of trees with exactly one PR in each tree. The solution determines the best possible destination for each RA.

The second model considers capacity constraints on PR nodes. Yamada uses a minimum cost network flow formulation to model this problem. He modified the original graph by adding a dummy source node (v_*), a dummy sink node (v^*), and a set of arcs connecting v_* to RA and v^* to PR nodes. The new network is denoted by $G^* = (V^*, E^*)$, where $V^* = V \cup \{v_*, v^*\}$ and $E^* = E \cup \{(v_*, r) \mid r \in R\} \cup \{(d, v^*) \mid d \in D\}$.

The following is the problem formulation:

$$\text{minimize } \sum_{(u,v) \in E} k(u,v)x(u,v) \quad (4)$$

subject to

$$\sum_{u \in V^*} x(u,v) = \sum_{w \in V^*} x(v,w) \quad \forall v \in V \quad (5)$$

$$\sum_{d \in D} x(d,v^*) = P \quad (6)$$

$$0 \leq x(u,v) \leq c(u,v) \quad \forall (u,v) \in E^* \quad (7)$$

where $k(u,v)$, $c(u,v)$, and $x(u,v)$ are the cost coefficient, the capacity, and the number of evacuees traversing arc (u,v) , respectively. P is the size of the population, and R is the set of RA nodes. Due to the capacity constraints, the solution may not be a forest of trees and, as a result, evacuees of an RA node may be assigned to multiple PR nodes that may not necessary be the closest. The SEP minimizes the total travel distance by routing evacuees to the closest exit. This approach causes congestion in certain exits, which in turn increases the total evacuation time. Cova and Johnson [9] overcame this difficulty by developing an optimal lane-based evacuation routing plan. They formulated the problem as an integer extension of the minimum cost network flow problem. The objective, again, is to minimize the total travel distance. However, the model generates routing plans that trade total vehicle travel distance against merging conflicts while preventing traffic-crossing conflicts at intersections. They use a microscopic traffic simulation to compare the relative efficiency of the plans. The model is then used to identify evacuation routing plans for Salt Lake City, Utah. The selection of a specific destination limits the route choices of evacuees and increases congestion of the roads that lead to safety. To avoid

congestion, Hobeika *et al.* [17] have developed a model that routes the evacuees to the outside boundary of the risk area and lets them seek a safe place afterwards. They have extended the traffic network by adding dummy links that connect the final destinations to the network at the boundary areas. The dummy links have infinite capacity and short travel time. The objective is to minimize the total evacuation time. Similarly to the trip departure step, human behavior significantly affects the destination choice of evacuees in emergency situations.

Evacuees may change their intended destination if they notice considerable traffic backed up ahead of them [35]. In situations when the household members are scattered throughout the evacuation area, the individuals' tendency to meet before evacuating affects the destination selection choice. Murray and Mahmassani [27] point out that depending on the current location of family members, evacuees may decide to meet in a place that is close to the danger rather than far from it.

2.1.4. Community Evacuation: Trip Route Selection

The trip route selection, also known as trip route assignment, identifies the movement of evacuees during the evacuation process. Numerous *optimization, simulation* and combinatory *optimization-simulation* approaches have been used to model route selection procedures in the last four decades. The most common objectives of these models are to minimize the total travel time, to minimize the total evacuation time, or to maximize the flow of evacuees from the risk area to safety [3, 9, 27, 28, 38]. The travel time depends on the speed of a vehicle on a highway segment. The average speed is a

non-increasing function of the traffic volume [15]. The following equation demonstrates the relationship between speed and volume and is referred to as the BPR (Bureau of Public Roads) equation.

$$SP_{it} = \frac{SP_i}{\left[1 + \alpha \left(\frac{V_{it}}{C_i}\right)^\beta\right]} \quad (7)$$

where, SP_i is the speed limit on segment i , SP_{it} is the average speed of a vehicle on segment i at time t , C_i is the capacity of segment i , V_{it} vehicle flow entering segment i at time t , α and β are constants.

Evacuation time depends not only on the traffic density, but also on traffic delays at inter-sections. The limited capacity, merging conflicts and crossing conflicts at intersections create un- avoidable bottlenecks. The lane-base routing approach, presented by Cova and Johnson [9] in 2003, speeds up the evacuating process by increasing the intersection capacity and alleviating conflicts. They formulate the problem as a minimum cost network flow problem that minimizes the total travel distance, considering intersection conflicts, lane changing, and left-hand turns, simultaneously. Murray *et al.* [27, 28] have formulated the evacuation routing as a vehicle routing problem (VRP). Unlike the classic VRP, they assume that vehicles have different capacities and are not located in a single depot but scattered throughout the network. In addition, the objective function minimizes not only the total travel time, but also the waiting time of evacuees at the meeting locations.

Besides *optimization* approaches, *simulation* based approaches have also been used to model evacuation routing. The employed route selection logic in simulation models might be simple, static or dynamic [35]. In a simple routing approach, the drivers either select the least congested route based on their myopic perception or follow some pre-determined set of routes. This approach has been used in microscopic simulation models such as CLEAR and NETSIM to simulate evacuation routing in small urban and rural areas [26, 30].

The static route assignment models assume that traffic conditions remain unchanged during the simulation period. A mesoscopic simulation package, DYNEV, developed by KLD Associates Inc., uses such models to create evacuation routing plans for large urban areas [21].

Considering the dynamic nature of emergency evacuation, the dynamic traffic route assignment models are superior to simple and static approaches [16, 17, 31, 32, 36]. To route the evacuees to safety, the dynamic routing approach does not follow a pre-determined set of turning movements at intersections; instead, turning movements are function of dynamic traffic flow and evacuee behavioral considerations. These behavioral considerations address a driver's prior knowledge of the best direction leading to safety and her/his myopic perception of traffic conditions.

In combinatory *optimization-simulation* approaches, an optimal route assignment model is integrated with a traffic simulation model. MASSVAC [17, 29] and Dynasmart-P [4] are examples of macroscopic simulation packages that rely on combinatory approaches. The objective of the optimization model in MASSVAC is to minimize the number of casualties. This model generates an optimal set of routes along with an optimal

evacuation schedule. Dynasmart-P is a dynamic traffic network analysis and evaluation tool that determines a time-dependent assignment of vehicles to different network paths. Thus, the assignment of a driver to a path is made not only based on the length of the path, but also evacuation time. The objective is to minimize the travel time for each individual traveler. A set of outflow constraints limits the total number of vehicles leaving the link at an intersection approach. Additionally, a set of inflow constraints limits the maximum number of vehicles allowed to enter a link from all approaches [19].

2.2. Building Evacuation

The issues discussed above are applicable in many emergency scenarios. However, the inevitable differences of some cases demand special considerations. Evacuating a building due to a disaster, such as the threat of smoke, fire, earthquake, bomb or toxic gas leak, requires a different approach. Lindell and Prater [22] have identified major differences between building and community evacuation. First, the social units within a building are not as clear as residential units within a community. Second, the employers can exercise more control strategies than public agencies. Finally, the departure time for building evacuation is shorter because of limited required preparation activities.

A number of studies have been devoted to describing the behavior of building inhabitants in emergency situations. For an extensive review, see Baker [1]. However, fewer studies have been conducted to model evacuation procedures. One of the earliest attempts by Chalmet *et al.* [3] uses a capacitated network flow problem as the basis for

modeling a building. Workplaces, halls, stairwells, and elevators represent the nodes of the network, and movement paths between them represent the arcs. The static capacity of nodes is the maximum number of individuals who are allowed to be in building components simultaneously. And the dynamic capacity of arcs is an upper bound on the number of individuals who can traverse the pathways in each time interval.

Chalmet *et al.* have used three different optimization models to solve the problem: a dynamic model, a graphical model and an intermediate model. The dynamic model is a multi objective optimization model that represents the evacuation as it evolves over time. In contrast, the graphical and intermediate models are not time dependent; they treat time as a parameter. They are simpler than the dynamic model; however, they provide almost the same insight about the building evacuation process.

The objectives of the dynamic model are to minimize the average number of time periods spent by each individual to evacuate the building, to maximize the total number of people saved, and to minimize the total evacuation time. The dynamic model is formulated as a minimum cost flow problem and efficiently solved using the GNET algorithm [2].

The graphical approach to model building evacuation was originally presented by Francis [13, 14]. The model assigns people to evacuation routes with the objective of minimizing the evacuation time. Two implicit assumptions of this model are that all evacuees have a uniform accessibility to the exit routes and that route clearance time depends on the number of people using the route. Given k to be the number of individuals in a building that has n exit routes, the formulation is:

$$\text{minimize } \max [t_j(x_j) | 1 \leq j \leq n] \quad (8)$$

subject to

$$x_1 + \dots + x_n = k \quad (9)$$

$$x_1, \dots, x_n \geq 0 \quad (10)$$

where $t_j(x_j)$ is the time required to clear route j if the total number of evacuees on this route is x_j . t_j is a continuous function and is strictly increasing with respect to x_j . Note that $t_j(0) = 0$. Considering the assumptions made by this model, the minimum evacuation time happens when all routes are cleared in the same time.

The intermediate model uses the same network structure as the dynamic model. However, it is superior to the dynamic model in view of the required input data and computational time. Similar to the dynamic model, the arcs are capacitated, but there is no traverse time on arcs. For a given subset A of arcs, called *critical arcs*, there is no capacity constraint; instead, the function $t_{ij}(x_{ij})$ estimates the time it takes to traverse arc $(i, j) \in A$ when the flow of evacuees on this arc is x_{ij} . Clearly, $t_{ij}(0) = 0$. The objective is to minimize the building evacuation time which is explained as minimizing the traverse time on critical arcs. A heuristic bisection search algorithm and an exact minimax algorithm were used to solve the problem.

2.3. Small-Area Evacuation

The standard approach for developing an evacuation plan for regions, buildings, ships, etc starts with determining the evacuation zone around a known hazard and then exploring some important factors that affect the evacuation plan (e.g., population distribution, road capacities and human behavior). To delimit the evacuation zone, a boundary is established around the affected area. In nuclear power plant evacuations, the boundary of the evacuation area is defined to X miles of radius from the plant, and X depends on the type of plant and the type of accident. In building evacuations such a boundary is defined by the shell of the building. However, for some emergency situations, such as urban firestorms or toxic spills on highways, the spatial impact of the hazard is unknown. In these kinds of situations, defining the evacuation zone and its boundary can not be done in advance. This is usually the case for the small urban and rural areas that could be subject to different hazardous events with uncertain spatial effects. Thus, the focus has been on general planning and mock drills rather than attempting to develop neighborhood specific evacuation plans. Cova and Church [10] were the first to analyze the potential for evacuation difficulty at the neighborhood scale.

Little is known about small area evacuation as it is nearly impossible to measure accurately during an emergency. But, there has been an interest in looking for those areas that might be difficult to evacuate safely in an emergency. Church and Cova [7] introduce a network-based model to search for small contiguous areas or neighborhoods, within an urban/rural area, that may face difficulties in a sudden evacuation scenario. Their model classifies a neighborhood based on the degree of evacuation difficulty. The evacuation difficulty is measured by the evacuation risk factor which is defined as the number of

vehicles per exit road. Church and Cova formulate the problem as a nonlinear network partitioning problem. The objective is to identify a critical neighborhood (critical cluster) that has the highest evacuation risk factor. In their network the nodes represent the households and the arcs represent the road segments connecting them. The demand of each node is estimated by multiplying the number of people per household with the average number of vehicles per person. The problem is transformed to an integer linear program whose objective is to identify an evacuation area that has a risk factor greater than a specific minimum threshold. This problem is solved for each node of the network. As a result, each node is labeled by the risk factor of its corresponding critical neighborhood. Finally, for each node the critical risk value is the highest value related to the critical clusters that this node has been part of. An exact and a heuristic approach are proposed to solve the integer-linear programming problem. Since the exact approach is time consuming, the heuristic approach is used to find a contiguous critical area around a given node. The heuristic approach follows a region growing basis. The base node is selected arbitrarily from the network. The area around the node is expanded iteratively by selecting a node randomly from a list of candidate nodes within a specific distance from the base node that most improves the objective function.

Cove and Church [10] have applied a similar methodology to generate an evacuation vulnerability map which classifies a local area based on the evacuation difficulty.

2.4. Real-Time Traffic Management

Real-time traffic management for emergency evacuation dynamically controls the traffic flow to achieve certain system objectives such as maximum utilization of transportation system and minimum fatalities and property losses. This approach considers the evolution of the traffic flow in a traffic network to generate a real-time feedback traffic management system by using in-vehicle and on route surveillance systems [5, 25]. Briefly stated, the current condition of dynamic traffic flow is *monitored* by surveillance systems and a reference model that generates the desired traffic status and the "safest evacuation strategy" is developed to satisfy the designated objectives. The objectives are defined based on the nature of the hazard and the involvement of the emergency authorities. Possible objectives are minimizing the total travel time, minimizing the network clearance time or minimizing the number of casualties. The generated real-time *control* strategies include routing assignments, split rates at intersections, or traffic control advisories that are passed on to evacuees cyclically. In fact, the control strategies are not necessarily practiced by all evacuees in emergency situations. Therefore, these strategies are *modified* based on the differences between the current traffic status and the desired traffic status defined by the reference model. The "monitor, control, and modify" framework is repeated frequently in a closed feedback loop to decrease discrepancies between the original plan and the current traffic status [25]. Some evacuation models include aspects of human behavior to provide more realistic control strategies that alleviate the deviations. The evacuation route choice model developed by Chiu *et al.* [5] is an example. This model replicates the route-selection procedure of evacuees when they are provided with safe evacuation routes. The

probability that an evacuee will select a particular route depends on his familiarity with the route, the degree of overlap between the routes and his preference of using freeways.

2.5. Agent-Based Modeling

Agent-based modeling is also known as individual-oriented modeling. This is an increasingly powerful modeling technique to simulate individual interactions in dynamic routing situations such as emergency evacuations. Agent-based modeling treats the individual vehicles as intelligent decision-making entities [11]. A model of agents and a model of their environment are two basic components of agent based modeling [39]. The behavior of an agent and its interaction with other agents is modeled by a set of rules such as accelerating, decelerating, and lane-changing rules. The traffic environment is modeled using a traffic network topology, road category, traffic lights, and traffic signs [12, 37].

In emergency evacuations, the agent-based simulation captures the collective behavior of agents, which greatly affects the evacuation plan. As a result, more realistic strategies are developed by including the individual behavior of evacuees and their interactions in panic situations. In 1993 Sinuany-Stern and Stern [34] used agent-based simulation for spontaneous urban evacuation. They examined the sensitivity of network clearance time to several traffic factors (such as interaction with pedestrians, intersection traversing time, and car ownership), and route choice mechanisms (such as shortest path selection or myopic-based selection). Cova and Johnson [8] assessed the spatial affect of a proposed second access road on household evacuation time using an agent-based

microsimulation model. Church and Sexton [6] used Paramics, agent-based microsimulation software, to simulate evacuation scenarios in a small neighborhood. They estimated the impact of different evacuation scenarios, such as opening an alternative exit, invoking traffic control plans, and changing the number of vehicles leaving a household, on evacuation time.

3. Conclusions

Emergency evacuation is a management strategy to ensure population safety in emergency situations. Communities, buildings, and residential areas are prone to disasters, thus detailed evacuation planning is necessary. Evacuation planning models consist of a five-step procedure that involves trip generation, trip departure time, trip destination, trip route selection, and evacuation plan set-up and analysis. We have presented here a summary of some noteworthy research on each of the above mentioned steps of the planning process. This review also focuses on the special features of community, building and small area evacuation planning. In addition, real-time traffic management and agent-based models are discussed. The real-time traffic management models consider the dynamic nature of traffic flow and generate a real-time feedback traffic management system in emergency situation. The agent-based models provide realistic emergency evacuation strategies by considering the individual behavior of evacuees (agents) and their interactions.

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CHAPTER III
MODELING THE ROUTING OF PUBLIC TRANSIT SYSTEM IN NO-
NOTICE EVACUATIONS IN URBAN AREAS

1. Introduction

Natural disasters (such as hurricanes, floods, earthquakes, etc.) or man-made disasters (such as nuclear power plant explosions, chemical spills, terrorist attacks, etc.) result in unfortunate events every year. Such extreme events necessitate the immediate or foreseen evacuation of a large population from the stricken area. In this context, no-notice evacuation is called when any unexpected incident occurs. No-notice evacuation is different from short-notice evacuation with prior notice, which comes from weather forecasting technologies or landfall prediction models. In short-notice incidents the severity and the location of the disaster are known *a priori*, while in no-notice evacuation, such as terrorist attacks, no such information is available. The lack of such information makes the no-notice evacuation process relatively complicated. A successful evacuation practice depends on the efficient utilization of the transportation and emergency response resources. For short-notice evacuation, the emergency management agencies have ample time (from 24-72) hours to select the practical evacuation practice among different possible strategies [41]. For no-notice disastrous situations, however, the

involved agencies shall practice the predetermined evacuation strategies immediately. The challenges that emergency management agencies usually face include making decisions related to the destination locations, the evacuation routes, the traffic assignment and the scheduled departure of evacuees [5]. These interdependent decisions are less complicated if we know the severity and the location of the incident at the time of the evacuation, which is the case for short-notice incidents. Conversely, for no-notice evacuation scenarios, the decision-making process becomes more critical and more complex.

In general, emergency evacuation of urban areas has gained prominent attention from both practitioners and researchers in the last three decades. In this context, efficient utilization of the transportation systems can mitigate the consequences of these incidents considerably. Among available modes of transportation, the use of public transit in evacuation situations is not well studied or understood. This is evident considering the stream of unfortunate events that have followed natural and man-made disasters. The recent experiences with Hurricanes Katrina and Rita have highlighted the need for urban evacuation and relocation planning for transit-dependent citizens. Transit-dependent citizens include people without access to private vehicles. In addition to people without vehicles, the indigent, the elderly, the infirm and tourists also rely on public transit system for evacuation. In New Orleans the number of people without access to private transportation is estimated to be as high as 25 to 30 percent of the population [41]. Bearing in mind the large transit-dependent population, busing is the most common mode of transportation in practice. Accordingly, the purpose of this study is to make the existing transit system viable transportation in emergency situations by developing a

practical “Public Transit Routing Plan” to deliver evacuees from the danger zone to the safe destinations. The evacuation destinations are designated safe locations that are adequately far from the danger zone. For each evacuation destination, there are numerous routes for the transit vehicles to follow. Determining how the evacuees can be evacuated to the safe destinations through utilization of the optimal public transit routing plan (PTRP) requires consideration of the traffic flow on routes, the capacity of transit vehicles and the available number of transit vehicles. A network flow model with side constraints can be used to address this problem. The model implicitly incorporates the prevailing traffic flow models on highways and arterial roads in order to calculate the traverse time on roads. Given the departure schedule of the transit vehicles, the resulting PTRP determines the optimal routes, along with the optimal destination assignment for the vehicles. The model is required to be solved efficiently in order to generate fast and reliable responses to no-notice incidents. To the authors’ best knowledge, analytical approaches that model the application of the public transit does not exist in literature and practice.

Prior to 1979, the models developed for evacuating people and vehicles from danger zones were mainly descriptive, i.e., how the incident affects the evolution of traffic flow. The incident at the Three Mile Island nuclear power plant near Middletown, Pennsylvania, in 1979 provided the major impetus to develop simulation-based models to assist the emergency evacuation planners to mitigate the resulting suffering and losses (Urbanik and Desrosier, 1981 [39]; Sheffi *et al.*, 1982 [33]; KLD Associates, 1984 [20]). These studies resulted in numerous prevalent simulation packages, such as DYNEV (KLD Associates, 1984 [20]), and TEDSS (Hobeika *et al.*, 1995 [14]). DYNEV is a

mesoscopic simulation package that has been used to estimate the evacuation time for several nuclear power plants. Like microscopic models, the mesoscopic models' unit of traffic flow is an individual vehicle. The movement of the vehicles, however, follows the approach of macroscopic models that depend on the average speed, density and flow on the travel link. TEDSS is an example of the microscopic simulation packages developed for the analysis, evaluation, and development of evacuation response plans around nuclear power plants.

With the strike of severe hurricanes such as Hurricane Hugo (1982), Hurricane Charley (2004) and Hurricane Ivan (2005), the practitioners and researchers became more focused on hurricane evacuation (Hobeika and Jamie, 1985 [16]; Hobeika *et al.*, 1985 [15]; Sherali *et al.*, 1991 [34]; Hobeika and Kim, 1998 [17]; Wilmot and Mei, 2004 [40]; ORNL, 1999 [28], COE, 2000 [7]). The conducted studies resulted in numerous simulation packages, including MASVACC, OREMS and HURREVAC. MASSVAC is a macroscopic simulation package designed for the analysis and evaluation of evacuation plans for urban areas threatened by natural disasters, such as hurricanes. MASSVAC is able to simulate different evacuation scenarios, evaluate various traffic management strategies, calculate the evacuation time and identify the most efficient routing plan from the danger zone to the safe location (Hobeika and Jamie, 1985 [16]; Hobeika *et al.*, 1985 [15]). OREMS is a microscopic simulation model designed to analyze and evaluate large-scale emergency evacuations for a variety of disasters, conduct evacuation time estimation studies, and develop evacuation plans (ORNL, 1999 [28]). A recent evacuation modeling package is the HURREVAC that was developed specifically for

hurricane evacuation. It estimates the time required to evacuate the stricken area, which helps emergency managers in the evacuation decision-making process (COE, 2000 [7]).

Perkins *et al.* have touched on the application of public transit in short-notice evacuation though the major focus of their research is to model transportation issues associated with hurricane evacuation planning. These issues include determining the total evacuation time, identifying the traffic bottlenecks, and assessing the traffic operation strategies in order to mitigate the traffic congestion [30]. They address an evacuation methodology specific to hurricanes that determines the schedule of buses to evacuate the elderly and disabled citizens in North Carolina's small urban and rural areas. They assume that buses are located at a single depot prior to evacuation. Each bus is assigned a pick-up point, where it loads the evacuees and follows a predetermined route to reach the safe locations.

By the increasing number of destructive incidents such as terrorist attacks and hazardous materials (hazmat) releases, with more than 1 major hazmat incident per day in the US, the researchers and practitioners have given more attention to no-notice evacuation [29]. The conducted researches, though increasing gradually, are limited to the specific facets of the evacuation practice.

Murray *et al.* have studied the psychological behavior of households before evacuation resulting from no-notice incidents. Their work addresses the tendency of households to gather and then evacuate as a single unit. They consider a scenario in which a household has an advance evacuation plan or the decision-maker makes a decision. For such a scenario, 2 linear integer programming formulations are used sequentially to model the household decisions regarding the meeting location and the

optimal schedule to meet. The first formulation determines the household meeting location while minimizing the maximum travel time of family members. The second formulation determines the route assignment along with the non-drivers' pick-up schedule by minimizing the linear trade-off between waiting time and travel time [25-27].

The household model is a static model in terms of traffic flow modeling. Chiu *et al.*, however, present a dynamic traffic flow optimization model that explicitly incorporates the dynamics of the traffic flow in a multidimensional environment in which decisions regarding the evacuees' evacuation directions and routes are made simultaneously. A solution to their model addresses 3 common evacuation-related decisions: (i) the selection of available safe destinations, (ii) the optimal routes from the danger zone to the safe destination along with the optimal traffic volume on each route, and (iii) the determination of optimal departure schedules for evacuees [5].

In this research we investigate how the public transit system can be utilized to evacuate transit-dependent citizens in no-notice incidents. The main contribution of this paper is that it proposes a network flow-based methodology to find the optimal public transit routing plan unique to no-notice evacuation. The problem itself, and also the proposed modeling methodology, is the first time practice published in the no-notice evacuation research literature. The proposed methodology is comprised of 2 stages: optimization and simulation. In the optimization stage, a mixed integer linear programming formulation is used to model the routing of the public transit system. The solution time is an important concern in no-notice incidents. Thus, the long running time of the exact solution approaches motivates the application of the heuristic TABU search algorithm to find comparable solutions in a considerably shorter amount of time. In the

simulation stage, a dynamic traffic network analysis and evaluation tool, DYNASMART-P, is used to evaluate the effectiveness of the developed PTRP.

The remainder of this paper is organized as follows. Section 2 explains the public transit routing plan (PTRP) problem, along with complexities involved in no-notice evacuation scenarios regarding evacuation zones and evacuation objectives. Section 3 presents the modeling approach for the PTRP problem. It explains the detailed procedure to build the time-space transit network. Section 3 also includes the mathematical formulation of the PTRP problem. Section 4 gives details of the heuristic TABU search algorithm which is used to solve the problem at hand. In Section 5 the proposed methodology is implemented on the traffic network of the city of Fort Worth to illustrate the proposed methodology. Finally, in Section 6, we close the discussion by providing concluding remarks on the problem and the future research potentials.

2. Problem Description

Evacuation process is called when natural or man-made disasters strike urban areas. Depending on the nature of the disaster and its severity, the population endures an immediate or foreseen evacuation. The foreseen evacuation is specific to short-notice incidents, such as hurricanes and flooding, in which the location and the severity of the incidents can be predicted using weather-tracking technology or landfall prediction tools. Alternatively, the immediate evacuation is caused by no-notice evacuation scenarios when there is no means to predict where and when the disaster happens. Such specific characteristics of the no-notice incidents contribute to the complexity of the problem.

This complexity affects the evacuation zone definition, the evacuation objectives and the solution approach.

2.1. Evacuation zone

The standard approach for developing an evacuation plan starts with determining the evacuation zone around a known incident. To delimit the evacuation zone, a boundary is established around the stricken area. In the case of flooding, for example, the evacuation zone can be derived by the estimated time when the area becomes inundated [5]. There are hydraulic analyses and models that can assist a planner in determining the evacuation zone. For special events, such as toxic spills on highways or terrorist attacks, however, the spatial impact of the hazard is unknown. This is usually the case for urban and rural areas that could be subject to different hazardous events with uncertain special impacts. Unfortunately, little research has been conducted in this area. Church and Cova proposed a network-based model called the “critical cluster” model to search for small, contiguous areas within urban/rural areas that face difficulties in sudden evacuation scenarios [6]. They classify a neighborhood based on the evacuation difficulty, which is measured by the evacuation risk factor. The evacuation risk factor, as they define it, is the number of vehicles per exit road. For nuclear power plants, there are some guidelines (NUREG-0369 and NURE-0654) that determine an area with a radius of 10 miles around the nuclear plant [36, 37]. This area is called the plume exposure pathway emergency planning zone, which forms the basis for the emergency planning of the plant. If any hazardous event, such as an explosion, is about to exceed the defined boundary, then protective actions, such as sheltering in place or evacuating, shall be practiced. However,

such guidelines may not be available for all type of incidents. In such circumstances, estimating the evacuation boundary requires the experts' opinion and the predefined operational policies of emergency management agencies [5]. In our model we assume that evacuation zone boundaries are *a priori* information provided by the experts and relevant emergency officials.

2.2. Evacuation objective

Evacuation planning necessitates making a great number of operational decisions. Southworth has modeled the evacuation planning as a five-step process that involves making decisions regarding trip generation, trip departure time, trip destination, trip route selection, and evacuation plan set-up and analysis [35]. The above-mentioned decisions are made based on numerous objectives. Some common objectives are to minimize the individual and total travel distance, to minimize the total evacuation time, or to maximize the flow of evacuees from the danger area to the safe area [3, 8, 42]. Murray *et al.* have modeled the evacuation routing problem as a vehicle routing problem with a combinatory objective function. In their proposed objective, they minimize not only the total travel time but also the waiting time of the evacuees [26, 27]. Chalmet *et al.* have proposed a dynamic model for the building evacuation that optimizes 3 related objectives simultaneously. Their proposed objectives are to minimize the average number of time periods spent by each individual to evacuate the building, to maximize the total number of people saved, and to minimize the total evacuation time [3].

Besides analytical models, simulation methodologies also consider different objectives. MASSVAC, for example, generates an optimal set of evacuation routes along

with an optimal evacuation schedule in order to minimize the number of casualties [15, 17]. DYNASMART-P, however, minimizes the travel time for each individual traveler to find the optimal time-dependent assignment of vehicles to different network paths [4].

For no-notice evacuation scenarios, the objective is either maximizing the number of people exiting the evacuation area or minimizing casualties or exposure to the danger environment given the evacuation operation horizon [5]. Because of the nature of no-notice incidents, people cannot remain in the danger location more than a specific period of time. For incidents such as chemical spills or radiological leaks, the human exposure time to the toxic environment is limited; otherwise, fatality is inevitable. In such circumstances, the critical issue is to increase the number of saved individuals rather than focusing on the evacuation time. To entertain such a concern, the objective function of our problem is twofold: maximizing the number of saved people as well as minimizing the evacuation time.

In this research we investigate how public transit can be used in practice in no-notice disaster situations. Public transit, or a mass transit system, is any system that transports members of the general public. In general, public transit includes rail and bus services; however, a wider definition would include scheduled airline services, ferries, taxicab services, etc. [32]. For the purpose of this research, our discussion of public transportation will be limited to the use of buses. Buses come in many varieties, from commuter buses (or city buses), to school buses with seats for 47 to 62 passengers, to minibuses with seats for up to 25 passengers. The transit riders usually run buses on regular fixed itineraries with fixed schedules and stops.

We provide a mixed integer linear programming formulation to solve the problem. Given the evacuation horizon, the objective is to have more people evacuated safely from the danger zone to safe destinations. The safe destinations are designated shelters far enough away from the danger zone to be considered safe. Public buildings such as schools, colleges, and churches that are sufficiently far from the disaster location and have ample space to accommodate evacuees may be considered as safe destinations. We treat the shelter location as a model input. The no-notice nature of the disaster implies that the location of the disaster and its relative severity are unknown ahead of time. Having this information in hand at the time of the disaster, the developed model is supposed to generate the transit evacuation routing plan shortly after the incident strike. The allure of finding the solution in a short amount of time motivates the application of approximate solution approaches when the exact solution approaches fail to find the solution shortly. Therefore, a meta-heuristic TABU search algorithm is used to generate a high-quality solution in an acceptable amount of time. The next section will provide a detailed description of the modeling and the solving approaches to the problem.

3. The PTRP Modeling Approach

Basically, the problem of determining optimal evacuation paths out of a danger zone can be modeled as a network flow problem. The objective is to evacuate more people from a set of source nodes representing transit stations to a set of exit nodes representing shelters in a given time frame without violating the capacity constraints of the system. These nodes are connected by directional links representing the arterial roads

and highways that indicate the permissible direction of the flow of vehicles during the evacuation process. Those links have attributes such as capacity (i.e., maximum flow that can traverse the link) and travel time that depend on the traffic flow and length of the link.

Here, we use a time-space network structure to present the schematic of the transit network. To do so, first we utilize the TranCAD software to extract the spatial structure of the urban transportation network. The resulting transportation network is an undirected graph in which nodes represent the road intersections (including transit stations and shelter locations) and arcs represent the road segments connecting nodes. Takeo Yamada has also used the same structure to model the city network in his network flow approach in city emergency evacuation planning [42].

Let $G=(V,E)$ be the undirected graph of the city, where V and E stand for the set of nodes and the set of arcs, respectively. The set V is decomposed as $V=I\cup I'\cup N$, where $I=\{s_1,s_2,\dots,s_n\}$ is the set of stations, $I'=\{sh_1,sh_2,\dots,sh_l\}$ is the set of shelters, and N is the set of intersections. Here, n and l are the number of stations and the shelters, respectively.

3.1. Build the Time-space Transit Network

For small, urban areas, the size of the traffic network (G) is relatively large, which adversely increases the size of the problem. Given the underlying idea behind this research that deals with the transit system, it is not required to look at the complexity of the traffic network. Therefore, the graph G transforms to the smaller time-space network $G^*=(V^*,E^*)$, where $V^*=\{I^*\cup I'\cup s^*\}$ denotes the node set and E^* denotes the arc set. The

network G^* , which is illustrated in Figure 1, consists of $T + 1$ layers, and each layer represents a time period. The time-space network contains 3 types of nodes: *StatNodes* (I^*), *ShelterNodes* (I'), and *SinkNode* (s^*). The *StatNodes* are the set of station nodes with two attributes: location and time. The location of the stations is defined based on the existing transit system. Time is discretized with respect to equal-length time intervals (*intertime*). Let the time period set be defined as $\mathfrak{R} = \{0, 1, 2, \dots, T\}$. For instance, if 1 hour is discretized into 10-minute periods, then $T=6$. Nodes of the set I^* correspond to the copies of each station nodes $i \in I$ in each time period $\alpha \in \mathfrak{R}$; in other words, the *StatNodes* corresponds to the set $I \times \mathfrak{R}$. An element of this set is denoted by i_α , where $i \in I$ and $\alpha \in \mathfrak{R}$. The demand of node i_α is equal to the number of individuals who arrive at station i at time period α .

The *ShelterNodes* set corresponds to the set of shelter nodes in which evacuees are accommodated temporarily. The supply/demand at shelter nodes is equal to zero. The feasibility condition of the network flow problem requires that the supply/demand at the nodes satisfy the condition $\sum_{n=1}^{|I^*|} b_n = 0$. Therefore, an artificial *SinkNode* is introduced, and its supply is set to the total demand on nodes in *StatNodes*.

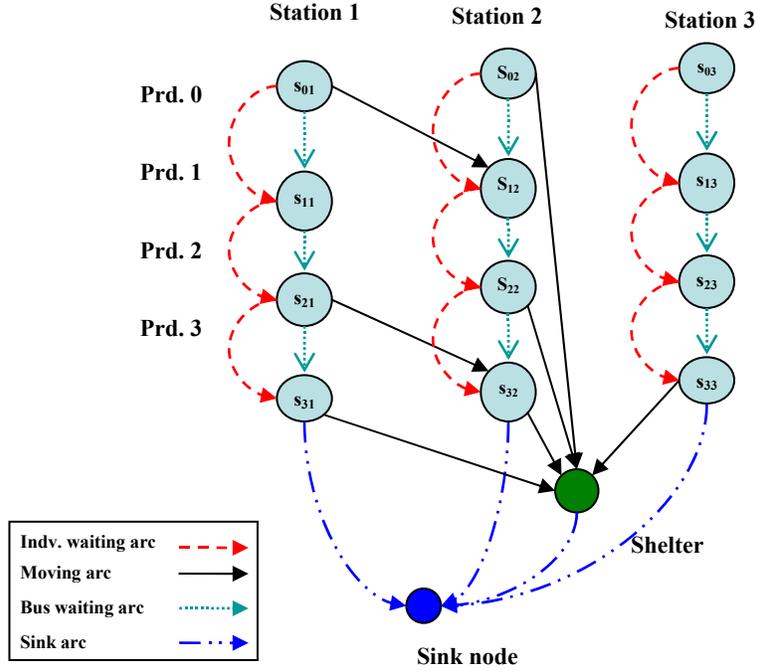


Figure 1

Topographical representation of a network with 3 stations, 1 shelter, and 3 time intervals

The set E^* of arcs is decomposed into 4 subsets: movement arcs (M), individual waiting arcs (W_p), transit vehicle waiting arcs (W_B), and sink arcs (S). The arcs in the set of movement arcs emanate from nodes in the *StatNodes* and enter nodes in *StatNodes* or *ShelterNodes*. To model a possible arc from station i at time period α to station j , we create an arc from node i_α to node j_β , where $\beta = \alpha + r_{i_\alpha, j} / inertime$ and $r_{i_\alpha, j}$ is the travel time between station i and station j at time α . Similarly, there is a movement arc from each node i_α in *StatNodes* to node j in *ShelterNodes*. The movement arc between any pair of nodes is selected out of k -dissimilar paths between nodes. At time period α , the travel

time on k -dissimilar paths from node i_α to node j is updated, and the one with the shortest travel time ($r_{i_\alpha j}$) is selected to connect node i_α to node j . The capacity of movement arcs is equal to the capacity of transit vehicles, and their cost is equal to the time required to traverse the path. One may define parallel movement arcs to allow for multiple vehicles traversing the same path, which is a reasonable option in reality.

The set of individual waiting arcs (W_p) includes the arcs from node i_α to node $i_{\alpha+1}$. Individuals at station i who are not picked up by any transit vehicle at time period α will move to the subsequent copy of station i at the next time period ($\alpha + 1$) using the individual waiting arc. The individual waiting arcs are uncapacitated and they can flow an infinite number of individuals from one time period to the next time period. Since most incidents make roads congested, it would be a reasonable option for transit vehicles to wait in stations to accumulate more people rather than moving around and most probably being trapped in traffic. Therefore, we introduce transit vehicle waiting arcs (W_B) from node i_α to node $i_{\alpha+1}$. Unlike individual waiting arcs, the transit vehicle waiting arcs are capacitated, and their capacity is limited to the vehicle capacity. The traverse time on both types of waiting arcs is equal to the length of the time interval (*intertime*). Clearly, there is no waiting arc leaving the last copy of stations (i_T). Similar to movement arcs, one may define parallel bus waiting arcs to allow multiple buses to wait at a station simultaneously.

The arcs in the set of sink arcs (S) emanate from the last copy of stations (i_T) in *StatNodes* and shelter nodes in *ShelterNodes* and enter the *SinkNode*. The sink arcs between nodes in *StatNodes* and the *SinkNode* are incapacitated, and their traverse time is

set to a big number to discourage the individuals to move to the *SinkNode*. The sink arcs between the shelter nodes and the *SinkNode* are also incapacitated; their traverse time, however, is set to be zero.

Some transit vehicle may be at stations located in danger zones at the time the evacuation order is released. Therefore, they start their trip at the first time period. Other transit vehicles, however, may be far from the evacuation zone and spend some time to reach the stations in evacuation boundaries. Once a transit vehicle arrives at a station, it can either leave the station after loading the evacuees or remain in the station to accumulate more evacuees while there is positive residual capacity for the vehicle.

K-dissimilar Paths: Depending on the severity of disaster, some paths may be blocked, or some part of the paths may be damaged. In this situation, it is desirable to generate backup paths in case the best path becomes inaccessible. Generating backup routes in emergency situation motivates the *k*-shortest paths problem. Numerous algorithms have been developed for generating *k*-shortest paths between 2 nodes of a network [31, 43]. The idea behind these algorithms is extracting the next shortest paths from the shortest paths that have been generated so far. By this approach, the resulting generated paths may be very similar to one another. The drawback of similar paths is that the blockage of one link adversely affects all the paths that share the same link. Thus, to assure the safety of evacuees in an emergency situation, it is preferable to generate a number of paths that have as few common links as possible. In literature, these paths are addressed as *k*-dissimilar paths (but not necessarily disjoint paths). For an extensive review of developed algorithms to solve *k*-dissimilar path problem, see Akgun *et al.* [1]. Among developed algorithms for generating *k*-dissimilar paths, we jointly implement

Iterative Penalty Method (IPM) and the discrete p -dispersion algorithm because of their implementation simplicity and high-quality solutions [19, 24].

The IPM has been suggested by Johnson *et al.* in the context of hazardous materials routing. In this context, the IPM method gives the best result among other algorithms [13]. The method is based on the repetitive application of the shortest path algorithm. Each time the algorithm finds the shortest path between an origin and a destination node, the length of all links in the resulting shortest path is penalized to encourage the algorithm to generate an alternative path. After generating a set of candidate paths using IPM, the discrete p -dispersion algorithm is used to select k -dissimilar paths out of m candidate paths ($1 < k < m$) such that the minimum dissimilarity between pairs of selected paths is maximized. Considering P_i and P_j as 2 arbitrary paths, the dissimilarity index between them (d_{ij}) is defined by the following formula [13]:

$$d_{ij} = 1 - \frac{\frac{L(P_i \cap P_j)}{L(P_i)} + \frac{L(P_i \cap P_j)}{L(P_j)}}{2} \quad (1)$$

where $L(P_i)$ is the length of the path P_i . Generally, the minimum dissimilarity index is decreased as the desired number of dissimilar paths increases.

Travel Time on Paths: Given the speed on paths, the travel distance is translated into the travel time. The travel time on a road segment depends on the speed resulting from the traffic density on the road [4, 21]. The relation between density and speed is best shown by the modified version of Greenshield's equation. Freeways and highways can accommodate a large number of vehicles close to free flow speed because of their

geometric design and the control access characteristics. Therefore, the two-regime model is used to estimate the speed on freeways and highways. To do so, equations (2) and (3) are used in free flow and congested flow conditions, respectively. Unlike freeways and highways, the arterial and street roads with more controlled intersections and interferences experience more traffic conflicts. The speed on these types of roads immediately deviates from the prevailing level as the density changes. As a result, the single-regime model properly explains the speed-density relation on arterial and street roads. This single-regime model is best described by equation (3). Following are the explained equations:

$$v = u_f \quad 0 \leq \lambda \leq \lambda_{breakpoint} \quad (2)$$

$$v = v_0 + (v_f - v_0) \left(1 - \lambda / \lambda_{jam}\right)^\alpha \quad \lambda_{breakpoint} \leq \lambda \leq \lambda_{jam} \quad (3)$$

where,

- v = mean speed on road section (mph)
- u_f = mean free-flow speed in free-flow conditions (mph)
- v_0 = user-specified minimum speed (mph)
- v_f = mean free-flow speed in congested-flow conditions (mph)
- λ = link density (veh/mile/lane)
- λ_{jam} = density at jam speed (veh/mile/lane)
- α = user-specified power term
- $\lambda_{breakpoint}$ = optimum density (veh/mile/lane)

The density on roads depends on the travel pattern of drivers in different situations [4]. In cases where the evacuees are provided with descriptive information about the location of the disaster, they try to avoid the roads that lead them to the disaster location; therefore, the background traffic of the evacuation zone will be less dense. However, if the travelers are not notified about the disaster location, they select roads that channel them toward the evacuation zone. This situation will cause blockage on roads and congested traffic in evacuation zones that results in high density on roads.

Demand Distribution: After introducing the planar presentation of the traffic network, the demand distribution is the next issue to address. Demand distribution defines the number of individuals who arrive at stations as the evacuation process continues. The distribution of demand depends on the potential population of the evacuation zone who actually rely on the transit system. This demand is not only space dependent but also time dependent [35]. In order to determine the total number of individuals who will arrive at a transit station, we need to define a service area for each station. One approach to delimit the service area is to apply the concept of Thiessen polygons [9]. A Thiessen polygon around a given point is a polygon whose boundaries define the area that is closest to that point relative to all other points. The Thiessen polygons centered at the station nodes are used to assign individuals coming from a contiguous area to their nearest station. By partitioning the network into adjacent polygons, individuals are assigned to their closest station located in the center of polygon. In our study, we use TransCAD to create Thiessen polygons around given station nodes. Finally, to estimate the total number of individuals at an aggregate level, the surface of

the service area corresponding to each station is multiplied by the population density. The population density has been collected from census data [2].

The total potential demand at each station is appropriately partitioned to determine the loading of individuals at each time period. To do so, we need to specify the arrival pattern of individuals at transit stations. The “mobilization curve” concept introduced by Jamei in 1984 is used to estimate the arrival rate of individuals at different time periods [18]. The mobilization curve is represented using the following equation:

$$C_t = 1/(1 + \exp[-LR(t-h)]) \quad (4)$$

where C_t is the cumulative percentage of individuals loaded in the network by time t , LR is the loading rate or the response rate of the public to the disaster order and is known as the slope of the mobilization curve, and h is the half loading time. Time *zero* is the time that the evacuation order is released.

The loading time of individuals is the time that they arrive at transit stations. The half-loading time is chosen as one of the input parameters. If the mobilization curve is used to present the cumulative loading of evacuees to the network, then by using a different half-loading time, one can affect the loading parameters according to disaster characteristics [17]. Therefore, making decisions regarding the half-loading time plays a crucial role in evacuation process. The loading time generally consists of the departure time and the time required to arrive at transit station. The departure time is the time that each person spends to get ready to evacuate once the evacuation order is released. In general evacuation scenarios, the departure time consists of the time required to receive

the official evacuation warning, the time required to leave the current location to get home, the time required to arrive home, and the time to prepare to leave home [38]. By this definition, the loading time varies based on the type of incident, the relative severity of the incident and the efficiency of the communication between people and involved emergency authorities. In this study we are not concerned with the departure time but the time that people arrive at the stations.

By introducing different loading rates in the implementation phase of the evacuation plan, different evacuation scenarios are developed. Generally, the low loading rate factor shows that more people response to the evacuation order at early stages, while the high loading rate states that a great number of evacuees spend some time for preparation prior to departure for evacuation purposes. For the low loading rate factor, people continue to show up at stations gradually during the evacuation time horizon; however, for the high loading rate factor, most of the people rush into the stations at the late stages of the evacuation process.

Once the network topology and the demand are both ready, the mixed integer linear programming formulation is used to formulate the PTRP problem. The formulation is discussed in the following section.

3.2. The MILP Formulation

Here the network flow formulation is used along with side constraints to formulate the PTRP problem:

$$\min \sum_{(i,j) \in E^*} t_{ij} x_{ij} \quad (5)$$

$$\sum_{\{j:(i,j) \in E^*\}} x_{ij} - \sum_{\{j:(j,i) \in E^*\}} x_{ji} = \begin{cases} \delta_i & i \in I^* \\ 0 & i \in I' \\ -\sum_{n=1}^{|I^*|} \delta_n & i = s^* \end{cases} \quad (6)$$

$$x_{ij} - u y_{ij} \leq 0 \quad (i,j) \in M \quad (7)$$

$$\sum_{\{i:(i,j) \in M\}} \sum_{j \in I} y_{ij} = \omega \quad (8)$$

$$\sum_{\{j:(i,j) \in \{M \cup W_B\}\}} y_{ij} - \sum_{\{j:(j,i) \in \{M \cup W_B\}\}} y_{ji} = b_i \quad (9)$$

$$-x_{ij} + u y_{ij} - M z_{il} \leq 0 \quad (i,j) \in M; (i,l) \in W_p \quad (10)$$

$$x_{il} - M(1 - z_{il}) \leq 0 \quad (i,l) \in W_p \quad (11)$$

$$y_{ij} \in \{0,1\} \quad (i,j) \in M \quad (12)$$

$$z_{il} \in \{0,1\} \quad (i,l) \in W_p \quad (13)$$

$$x_{ij}, x_{il} \geq 0 \quad (i,j) \in E^*; (i,l) \in W_p \quad (14)$$

where,

I^* = *StatNodes*

I' = *ShelterNodes*

S^* = *SinkNode*

M = set of movement arcs

W_P = set of waiting arcs for individuals

W_B = set of waiting arcs for transit vehicles

S = set of sink arcs

E^* = $\{M \cup W_P \cup W_B \cup S\}$

ω = total number of available transit vehicles

U = capacity of a transit vehicle

δ_i = supply at node $i \in I^*$

b_i = number of transit vehicles that start their trip from node $i \in I^*$

x_{ij} = Presents the flow of evacuees on movement arcs from node $i \in I^*$ to node $j \in \{I^* \cup I'\}$

x_{il} = presents the flow of evacuees on individual waiting arcs from node $i \in I^*$ to its subsequent copy (node $l \in I^*$)

y_{ij} = a binary variable related to the movement arcs that takes the value 1 if there is a flow of evacuees from node $i \in I^*$ to node $j \in \{I^* \cup I'\}$ and takes the value 0 otherwise

z_{il} = a binary variable related to the individual waiting arcs that takes the value 1 if there is flow of residents from node $i \in I^*$ to its subsequent copy (node $l \in I^*$) and takes the value 0 otherwise

The objective function (5) aims to minimize the total system travel time as well as the waiting time. Constraint set (6) is comprised of 3 sets of constraints. Each set

provides the standard flow conservation constraints for the nodes in *StatNodes*, *ShelterNodes* and *SinkNode*, for which the demand/supply are b_i , zero and $\sum_{n=1}^{|I^*|} b_n$, respectively. Constraint set (7) determines the transit vehicle capacity constraint. These constraints guarantee that, at any time, transit vehicles cannot move more individuals than their capacity. These constraints also connect the binary variables y_{ij} to their corresponding x_{ij} variables. Constraint set (8) limits the total number of transit vehicles to the number of available transit vehicles. Constraint set (9) indicates that, for a given time period, the total number of vehicles that leave a station deducted from the number of vehicles that enter the same station is equal to the number of vehicles that start their trip from that station at that time period. Constraint sets (10) and (11) ensure a vehicle does not leave a station with positive residual capacity while there are individuals waiting at the station. Constraint sets (12) and (13) are the binary constraints, and the constraint set (14) is the non-negativity constraint. The MIP solver, CPLEX, is used to solve the MILP formulation of the problem. The computational time of the problem, however, increases exponentially as the problem size increases. The long running time of the exact solution approach motivates the application of an approximate solution approach.

4. The PTRP Solving Approach

The TABU search algorithm is currently one of the most effective local search algorithms designed to find a near-optimal solution to many combinatorial optimization problems [11, 12]. Briefly stated, the algorithm generates a feasible solution S and then iteratively searches for a new neighbor S' to which to move. The move function transforms S into S' even if S' is not a better one. Since S' does not necessarily improve upon S , a TABU mechanism is implemented in order to prevent cycling over a sequence of solutions. One way to prevent cycles is to use a TABU list in order to keep some attributes of the past solutions and to reject any solution possessing these attributes. The elements of the TABU list define moves that cannot be applied currently. The list content is refreshed each time a new solution is found. The size of the TABU list is bound by parameter ζ that is required to be tuned. When the size of the list is equal to ζ , the oldest element is removed and the new one is added. A neighbor S' is chosen if it does not include elements of the TABU list or if an *aspiration criterion* is met. The *aspiration criterion* revokes the TABU status of a move if this yields a better solution than the best sought solution.

To design a TABU search algorithm, it is important to start by defining its fundamental elements. The elements of the TABU search algorithms are defined to be the initial solution, the neighborhood of a solution, the move strategy to a neighboring solution, the TABU list, the evaluation criterion, and the stopping criterion.

4.1. Initial Solution

The underlying idea of the proposed evacuation transit routing plan is to minimize the total evacuation time. The total evacuation time will be minimized if the greatest possible number of evacuees is evacuated at the earliest time possible. In the construction phase a feasible solution is built step by step by incorporating the same idea.

The procedure starts by randomly selecting one of the available transit stations, i , from the list of stations, I^* . Then the procedure continues by identifying the *next* station that is not only accessible from the current station but also provides the maximum accumulated number of evacuees, $MaxEvac$. At each step the procedure takes into account the available transit vehicle capacity, Cap . In cases where there is no residual capacity or there are no accessible stations from the current station, the procedure terminates by selecting the closest shelter and moves the evacuees to the closest shelter. Figure 2 presents a detailed description of the construction procedure.

Procedure Construct

For ($b = 1, \dots, NrVehicles$) **do**

Visit station i randomly

$I^* := I^* - \{i\}$

Update the vehicle residual capacity, Cap_b

While ($Cap_b > 0$ and accessible station from station i)

Visit the *next* accessible station with *MaxEvac*

Update Cap_b

$i :=$ *next* accessible station

End while

Visit the *closest* shelter to station i

End for b

Return the current solution S^\dagger

End Procedure

Figure 2

The construction procedure

† S is the set of stations visited by transit vehicles.

4.2. Neighborhood Definition

By definition, a solution S' that does not include TABU moves is the neighbor of solution S if it is feasible to the problem and it represents an adjacent flow. Here, two flows are adjacent if and only if they differ only on a sub-path between 2 stations. We construct a neighboring solution using 2-exchange and 3-exchange search mechanisms. The 2-exchange search mechanism constructs a neighboring solution S' by identifying an alternative sub-path between 2 stations i, j such that $(i,l), (l,j) \in S$. The 3-exchange mechanism constructs a neighboring solution S' by identifying an alternative sub-path between 2 stations i, j such that $(i,l), (l,k), (k,j) \in S$. Generally, the 3-exchange search mechanism explores a larger neighborhood than the 2-exchange search mechanisms.

Figure 3 shows the schematic of moving from an existing feasible solution to a neighboring solution using a 2-exchange search mechanism.

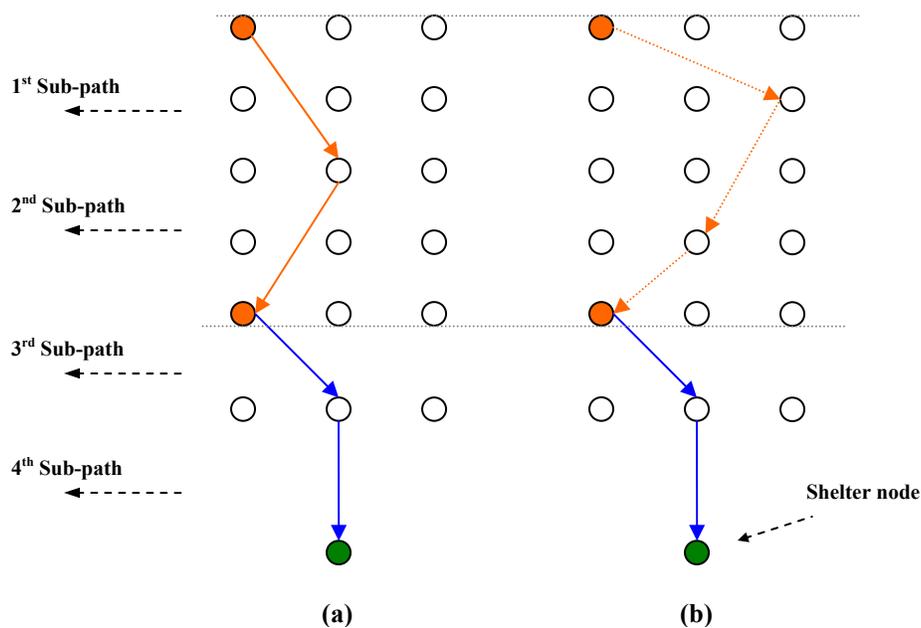


Figure 3

An example of moving to a neighboring solution: (a) initial feasible solution, (b) 2-exchange neighboring solution

4.3. Move Strategy

The *move strategy* determines the rule for selecting the next neighboring solution. There are primarily 2 move strategies: the first better and the best admissible. In the first better move strategy, the neighboring solutions are investigated in a predetermined order, and the first solution that shows an improvement is selected as the next solution. Clearly, the order of investigation affects the quality of the solution and the computational time. In the best admissible move strategy, the entire neighborhood is searched exhaustively, and the best solution is selected as the next solution. Since this is an exhaustive search, the sequence of the search does not affect the solution quality and the computational time. The best move strategy may lead to a better solution, but the exhaustive search is

not computationally efficient. In our case, the 3-exchange search mechanism explores a relatively large neighborhood; therefore, we implement the first better move strategy.

4.4. TABU List

In our algorithm we use the *TABU list* (\mathbb{T}) defined as a finite list with fixed size containing TABU sub-paths. We keep the same TABU list for the 2 different exchange mechanisms. The elements in the TABU list indicate whether selecting a sub-path between 2 stations is allowed or not. Given stations i and j , 2-exchange and 3-exchange mechanisms are defined such that $(i,l), (l,j) \in S$ and $(i,l), (l,k), (k,j) \in S$, respectively. In order to find an alternative sub-path between stations i and j using any exchange search mechanism, we need to make sure that the alternative sub-path is not listed in the TABU list (in other words, it is not a TABU sub-path). A TABU sub-path between stations i and j can be indicated as $(i,k), (k,l), (l,m), \dots, (p,q), (q,j)$. As the term suggests, the TABU sub-path between stations i and j has the station i as the upstream node and the station j as the downstream node. The TABU sub-path may include any number of connected links. The TABU list is updated each time an exchange mechanism is implemented. For example, stations i and j are currently connected via station r (that is, $(i,r), (r,j) \in S$). By implementing a 2-exchange mechanism, an alternative sub-path $(i,s), (s,t), (t,u), (u,j)$ is found that is not listed in the TABU list and is able to improve the *evaluation criterion*. Therefore, the existing sub-path between stations i and j is replaced by the new sub-path $((i,s), (s,t), (t,u), (u,j))$ and the sub-path $(i,r), (r,j)$ is added to the TABU list. Since the size

of the TABU-list is bound by l , when the $|T| = l$, the new one is added after removing the oldest one.

4.5. Evaluation Criterion

The TABU search algorithm implements the different exchange search mechanisms to find a better solution. Based on the first better admissible strategy, the first neighboring solution that improves the *evaluation criterion* is selected as the better solution. We simply define the *evaluation criterion* to be the total evacuation time that is the value of the objective function.

4.6. Stopping Criterion

The TABU search algorithm implements the 2-exchange and 3-exchange search mechanisms for the fixed number of iterations, consecutively. The algorithm initially starts with the 2-exchange search mechanism and explores the neighborhood of the current solution. If no better neighboring solution is found, then it moves to the best neighboring solution, even if it does not improve the current solution. Such moves are known as bad moves. After making a fixed number of bad moves, the algorithm switches to the 3-exchange mechanism. The algorithm stops by reporting the best found solution over all iterations.

4.7. Description of the Algorithm

The discussed elements are combined to implement the TABU search algorithm that is summarized in Figure 4. The TABU search algorithm is implemented for a fixed number of iterations (*MaxCounter*). At any iteration, the parameters are initialized and a random construction procedure is used to build an initial feasible solution. Then, the 2-exchange search mechanism starts with this initial solution and iteratively identifies the most appropriate neighbor to move. Next, in order to diversify the search, the 3-exchange search mechanism is performed. The TABU mechanism allows neighbor S' to be selected (bad move) even if it is not a better solution compared to S . By operating this way, the search mechanism explores the solution space beyond the local optimal. Finally, the algorithm terminates by reporting the best found solution over all iterations (S^*). The *MaxCounter* is one of the parameters that must be tuned.

Procedure TABU search

Step 0 : Initialize all the parameters

Find an initial solution S using **Construction** procedure

Step 1 : Perform the 2-exchange search mechanism

Step 2 : Perform the 3-exchange search mechanism

Step 3 : **If** $Counter < MaxCounter$, **then**

$Counter := Counter + 1$, go to **Step 1**

Step 4 : Return S^*

Step 5 : **End Procedure**

Figure 4

The TABU search algorithm

The procedure of the 2-exchange search mechanism is presented in Figure 5. The 3-exchange search mechanism follows the same procedure. The 2-exchange search mechanism randomly explores the neighbors of the current solution S to identify a solution S' to which to move. The solution S' is selected for further exploration if it is not TABU.

In this process, the algorithm keeps track of the current feasible solution (S), the best neighboring solution found (S_{nb}), the best solution found so far (S^*), and the number of visiting neighbors (NR_{cn}). For each solution, the corresponding objective value is calculated. If the objective value of the S' is smaller than the best objective value found so far, first we update the best solution S^* , then we move to this neighboring solution,

update the TABU list (\mathcal{F}), set the number of visited neighbors (NR_{cnt}) to zero and start the search for the new neighboring solution. We also move to S' if its objective value is less than the objective value of the current solution but not smaller than the best objective value found so far.

In order to diversify the search, we also allow moving to a worse neighboring solution. If solution S' does not improve the objective value upon S , first the number of visited neighbors is increased by 1. Then the best neighboring solution (S_{nb}) is updated if the objective value of S' is less than the objective value of the S_{nb} . When the maximum number of neighbors ($MaxNR$) is visited, the algorithm makes a bad move by moving to the best found neighboring solution. By operating this way, we avert the possibility of the search process from being trapped in a single unsatisfactory local optimum. The 2-exchange search mechanism is continued by the 3-exchange if the number of bad moves reaches the $MaxBad$. The $MaxNR$ and $MaxBad$ are 2 other parameters of the TABU-search algorithm that must be tuned.

Procedure 2-exchange

- (a) Initialize all the parameters
- (b) Generate S' , a neighbor of S using the 2-exchange mechanism
- (c) **If** $S' \in F$ **then** go to (b)
- (d) Calculate the objective value of S' ($objVal_{S'}$)
- (e) **If** ($objVal_{S'} < objVal_S$) **then**
 - If** ($objVal_{S'} < objVal_{S^*}$) **then** $objVal_{S^*} = objVal_{S'}$; $S^* = S'$; go to (i)
- (f) $NR_{cnt} := NR_{cnt} + 1$
- (g) **If** ($objVal_{S'} < objVal_{S_{nb}}$) **then** $objVal_{S_{nb}} = objVal_{S'}$; $S_{nb} = S'$;
- (h) **If** ($NR_{cnt} > MaxNR$) **then** $badMove_{cnt} := badMove_{cnt} + 1$
- (i) Move to S' ($S = S'$) ; update the F ; $NR_{cnt} = 0$; $objVal_{S_{nb}} = \infty$
- (j) **If** $badMove_{cnt} < MaxBad$ then go to (b)
- (k) Go to **Step 2** of the TABU search algorithm

Figure 5

The procedure of the 2-exchange mechanism

5. Case Study

This section provides a case study to illustrate the modeling techniques discussed in the previous sections. The test traffic network is the south-central part of the urban area in the city of Fort Worth, Texas. DYNASMART-P, traffic assignment and simulation software, provides the network framework for this application. The network has been illustrated in Figure 6. It is a directed network with 180 nodes, 445 arcs, and 13 traffic zones. Regarding the public transit system, there are 18 stations located in this part of the city, and the transit vehicles follow 5 itineraries, visiting stations based on a defined schedule from 5 a.m. to 11 p.m.

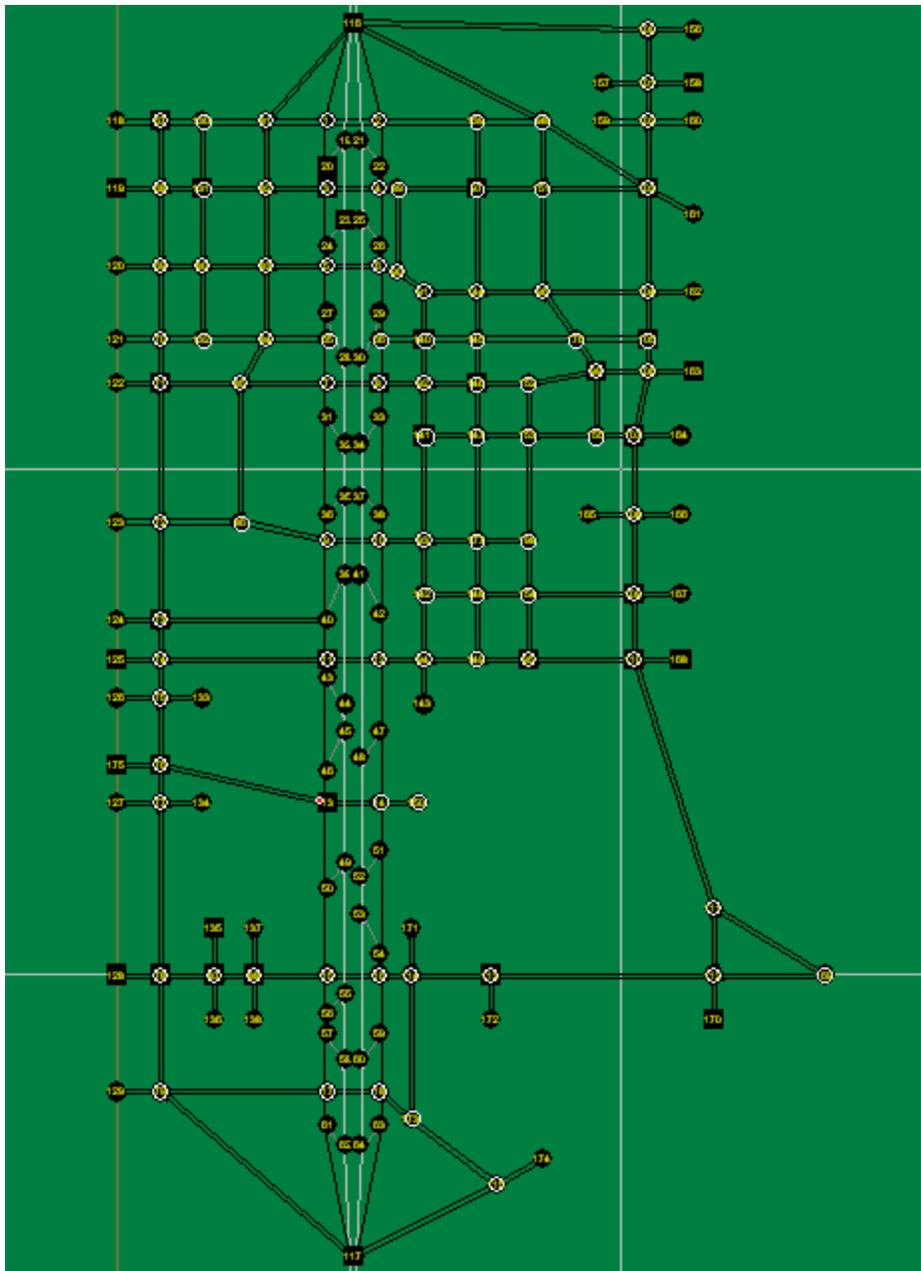


Figure 6

Traffic network of the city of Fort Worth, TX

The analysis of the PTRP problem involves several steps. In the first step, it is necessary to determine the area stricken by the no-notice incident (that is, the area to be evacuated to avoid any human fatalities). A hypothetical event is developed to test the PTRP modeling strategy. It is assumed that a hypothetical incident happens in the northwest part of the network. The scenario consists of an extreme explosion happen to a vehicle carrying hazmats, creating a plume of hazardous materials. The plume dispersion patterns can be obtained by using meteorological plume dispersion models. Here, the evacuation area involves the metropolitan area with a radius of 1 mile around the incident location. There are 6 stations located in this area that are supposed to be visited by the transit vehicles during the evacuation process. 2 end points of the network, which are sufficiently far from the incident location, are considered shelter locations.

In the second step, given the locations of the stations, it is necessary to find the shortest path connecting the stations. The shortest path is selected from k -dissimilar paths between pairs of stations. We apply the IPM method jointly with the p -dispersion method to generate k -dissimilar paths. The detailed procedure is explained in Section 3. To implement the penalty mechanism of IPM method, the following factors shall be determined:

- Penalized unit: the penalty can be applied on links, nodes, or both.
- Penalty structure: the penalty structure can be additive (adding a fixed amount to the impedance) or multiplicative (multiplying the impedance by a coefficient greater than 1).
- Penalty weight: the penalty weigh can be low or high (Assigning a very low penalty to the impedance encourages the model to maximize the use of penalized units. Larger penalties, on the other hand, discourage the appearance of the penalized units in alternative paths.)

- Penalized paths: the penalties can be applied to the last generated path or to all paths that have been generated so far.

In our experiment, we apply a multiplicative penalty structure to penalize the links. Since the links are directional, the penalty is applied to one direction to discourage travel in one direction only. At any iteration, we penalize the links of the most recently found path by 10 percent. If a repeated path were generated in any iteration, it is rejected. However, it would be penalized like other paths. We generate 10 dissimilar paths between pairs of stations and apply the p -dispersion algorithm to find 3 paths out of 10 in order to maximize the minimum dissimilarity between paths.

The third step requires that the road distance is converted into road travel time. To do so, equations 2 and 3 are used jointly to estimate the travel time on roads as a function of density. For the arterial and street roads, the model parameters are defined as $V_0 = 6$ mph, $\lambda_{jam} = 120$ veh/mile/lane, and $\alpha = 1.25$. Similarly, for the freeways and highways, the parameters are defined as $u_f = 92$ mph, $V_0 = 6$ mph, $\lambda_{breakpoint} = 30$ veh/mile/lane, $\lambda_{jam} = 200$ veh/mile/lane, and $\alpha = 2.73$. The abovementioned parameters are similar to the parameters of the traffic flow models of DYNASMART-P. To calculate the traverse time on roads, the abovementioned parameters are used along with the density information on roads. The density on roads is one of the output files generated by DYNASMART -P. It includes the density on all road segments at each time period.

By having the topology of the network, the fourth step is to determine the population at risk—not only their demographic distribution but also their response time to the evacuation order. To estimate the number of people at each station, first we use TransCAD to determine the area closest to each of the stations by building service areas

around stations. Then, by multiplying the surface of the service area associated with each station and the population density of the city, the potential number of individuals at each area is calculated. The population density can be estimated using demographic information. Most metropolitan planning organizations in US urban areas maintain and update such information.

Out of the entire population estimated at each service area, a percentage of the population relies on the transit system for evacuation purposes. We examine different percentages ranging from 5 to 20 percent with 5 percent increments. Then, the volume of the population that would be loaded onto stations must be determined in each time period. The total number of the transit-dependent population for each station is partitioned appropriately to determine the loading volume in each time period. Equation 4 is used for this purpose. The loading factor and the half loading time are input parameters that must be defined in advance. For the case of no-notice incidents, such as a nuclear power plant explosion, the quick loading factor of 0.04 has been used in literature [17]. The same loading factor is used for this case study. For nuclear accidents, the half-loading time of 1 hour has been used [17]. We consider 2 different evacuation scenarios with 0.5 and 1 hour as the half-loading time; therefore, the evacuation operation horizon is assumed to extend for 1 hour and 2 hours, respectively. The disaster is assumed to happen at time 0, which requires the no-notice evacuation to begin immediately.

We generate 2 base case problems using 2 different evacuation operation horizons and then alter the base case problems to generate different problems. For both cases, we define the following characteristics: $|I| = 18$, $|I'| = 2$, $U = 50$, and, for the k -dissimilar paths, we set $k = 3$. Here, we assume that the total potential demand at each transit station

follows uniform distribution. For example, if the average number of transit-dependent individuals at station 1 is equal to 100, then the $U_{\text{indv}} \sim [80-120]$. For each case we consider 4 sub-problems based on 4 different transit-dependent factors, 5%, 10%, 15%, and 20%. Then we try 3 different numbers of available transit vehicles (ω) for each sub-problem. As a result, there would be 24 problem instances that are repeated 10 times each. We assume that transit vehicles that are related to the same station arrive at the station sequentially with 1 minute time difference. For the first (second) evacuation scenario, a total of 44192 (89021) decision variables and 42088 (84757) constraints are created.

The MILP formulation of the PTRP problem is programmed in the C++ language, and CPLEX 9.0 callable libraries are used to solve the problem. Initially, we set the error gap to be 0.01. The error gap is calculated as $(z^{IP} - z_{LB}^{LP}) / z^{IP} \times 100$, where z^{IP} is the optimal objective value of the mixed-integer program. If z^{IP} is unknown, the objective value associated with the best known integer feasible solution is used instead. The value z_{LB}^{LP} is the best objective value among active LP sub-problems upon termination. In most instances the CPLEX runs out of memory after running for 3 days without reporting the optimal solution. Later, we limited the running time of the CPLEX to 5,000 CPU seconds. It is a reasonable time limit since the reported gap for 5,000 seconds does not significantly differ from the one reported after 3 days.

The same problem instances are used to test the performance of the TABU search algorithm. The TABU search algorithm involves 3 parameters that must be tuned: the total number of iterations, *MaxCounter*; the size of the neighbor list, *MaxNR*; and the maximum number of allowed bad moves, *MaxBad*. The parameter values used in the

heuristic algorithm are set to the following values after tuning: $MaxCounter = 30$, $MaxBad = 2$; for 3-exchange, $MaxNR = 10$, and for 2-exchange, $MaxNR = 5$.

For a heuristic approach, one is interested in evaluating how close the solution value is to the solution derived from the CPLEX. We introduce 3 measures of effectiveness for evaluation purposes: the computational time, the evacuation time (ET) and the evacuees' gap (EG). The evacuation time is the time that the last transit vehicle reaches the safe location. The evacuees' gap is calculated as $(P_{\%saved} - A_{\%saved}) / P_{\%saved} \times 100$, where $A_{\%saved}$ is the actual percentage of evacuees who are evacuated safely from the incident location. Given the number of available transit vehicles (ω), the value $P_{\%saved} = (\omega \times U) / \text{number of evacuees}$, is the percentage of evacuees who are planned to be saved. As an example, if $\omega = 3$, $U = 50$, number of evacuees = 300, and number of saved people = 125, the $P_{\%saved} = (3 \times 50) / 300 \times 100 = 50\%$, $A_{\%saved} = 125 / 300 \times 100 = 42\%$ and $EG = (50 - 42) / 50 \times 100 = 16.67\%$

A comparison of computational performance on 4 sub-problems is illustrated in Tables 1 and 2 for 1-hour and 2-hour evacuation operation horizons, respectively. The first 2 columns identify the problem instances by the percentage of transit-dependent people and the number of available transit vehicles. Columns 3 through 7 summarize the performance of CPLEX alone, and columns 8 through 12 summarize the performance of the heuristic TABU search algorithm. In columns 3 and 8, Time Elapsed (s) records the CPU seconds elapsed upon termination of CPLEX, either at optimality or when the process reaches the maximum allowed time of 5,000 CPU seconds or upon termination of the TABU search. Columns 4 and 9 include the evacuation time (ET) in minutes. The

evacuation time is the time that it takes the last transit vehicle to reach the safe location. Columns 5 through 7 and 10 through 12 record the actual percentage of saved evacuees ($A_{\%saved}$), the planned percentage of saved evacuees ($P_{\%saved}$), and the evacuees' gap (EG) for the CPLEX and TABU search, respectively. The results reported for each problem are averaged over 10 problem instances.

Table 1

CPLEX vs. TABU search algorithm for 1-hour evacuation horizon

Problem		CPLEX					TABU Search				
Transit Dep. (%)	No. of Buses	Time Elapsed (s)	ET (min)	A _{%saved} (%)	P _{%saved} (%)	EG (%)	Time Elapsed (s)	ET (min)	A _{%saved} (%)	P _{%saved} (%)	EG (%)
5	3	5009	10	35	35	0.00	7	12	35	35	0.00
5	5	5009	34	59	59	0.00	28	30	56	59	5.28
5	10	5024	61	99	100	1.29	123	61	98	100	2.44
10	6	5023	10	35	35	0.00	11	12	35	35	0.00
10	14	5028	53	82	82	0.66	78	50	80	82	2.61
10	20	5024	63	97	100	2.60	305	62	96	100	4.40
15	6	136	4	23	23	0.00	4	4	23	23	0.00
15	23	5024	56	87	87	0.05	147	53	85	87	2.16
15	30	5038	62	99	100	1.43	463	62	98	100	1.59
20	15	5021	16	43	43	0.11	26	16	42	43	1.11
20	31	5009	55	88	88	0.05	176	57	86	88	2.21
20	40	5022	63	96	100	3.56	470	62	98	100	1.67

Table 2

CPLEX vs. TABU search algorithm for 2-hour evacuation horizon

Problem		CPLEX					TABU Search				
Transit Dep. (%)	No. of Buses	Time Elapsed (s)	ET (min)	A% _{saved} (%)	P% _{saved} (%)	EG (%)	Time Elapsed (s)	ET (min)	A% _{saved} (%)	P% _{saved} (%)	EG (%)
5	3	5047	43	29	30	2.27	63	43	29	30	2.33
5	5	5065	70	49	49	0.12	148	62	48	49	2.88
5	12	5035	121	97	100	2.61	900	121	95	100	4.54
10	5	5158	38	25	25	2.29	67	35	24	25	2.36
10	10	5023	63	49	49	0.12	207	60	45	49	7.88
10	20	5015	122	94	99	4.85	1080	121	91	100	8.37
15	6	5093	34	19	20	3.90	59	27	19	20	4.67
15	16	5078	63	52	52	0.09	311	63	49	52	4.53
15	35	5039	125	92	100	7.90	1186	122	98	100	2.48
20	8	5177	31	19	19	0.25	61	28	19	19	0.50
20	17	5039	53	40	40	0.06	267	53	39	40	4.29
20	45	5013	124	90	100	9.79	1202	122	98	100	1.84

Regarding the computational time, as it is shown in Tables 1 and 2, the average CPU time of the heuristic TABU search is significantly lower than that of CPLEX. It should be noted that, for no-notice evacuation modeling, the developed model shall be solved efficiently to get the solution quickly after the incident occurrence. For the first scenario, all problem instances are solved in less than 8 CPU minutes. For the second scenario, most problem instances are solved in less than 5 CPU minutes. However, there are relatively large problems associated with the second scenario that are solved in 20 CPU minutes. The relatively large size of those problems causes the heuristic TABU search to investigate a large neighborhood for a longer time.

Another observation about Tables 1 and 2 is with respect to the evacuation time (*ET*) and the evacuees' gap (*EG*). It is desired to have a short evacuation time along with a small evacuees' gap. Therefore, it is necessary to analyze these interdependent measures simultaneously. As an example, for the first problem instance of the first scenario, as indicated in Table 1, the evacuation time is 10 minutes, and the evacuees' gap is 0.00 percent (i.e., the last transit vehicle reaches the safe location 10 minutes after the start of the evacuation operation, while as many individuals are saved as has been planned). As the result from Tables 1 and 2 indicate, the evacuation time derived from the heuristic TABU search is very close to that of the CPLEX. In addition, for a given evacuation time, the evacuees' gap reached by the heuristic TABU search is comparable with the evacuees' gap derived from CPLEX. Table 2 indicates some promising results, where the heuristic TABU search algorithm is able to generate evacuees' gap considerably smaller than that of CPLEX along with a smaller evacuation time: (2.48% (122 min.) compared to 7.90% (125 min.); 1.84% (122 min.) compared to 9.79% (124

min.). A comparison of results in Tables 1 and 2 indicates that the computational time of the TABU search algorithm increases as the problem size increases. Therefore, the TABU search is recommended for small and moderate size problems in which it shows great computational advantage over CPLEX.

For planning purposes, the responsible agencies would like to know the required number of transit vehicles to evacuate the entire population safely for a given evacuation planning horizon. If the agencies are provided with this information they can respond to disastrous situation proactively rather than passively waiting for the incident to happen. In order to predict the number of required transit vehicles, we assume that vehicles are dedicated to each station. Therefore, the total number of individual who show up at each station is divided by the capacity of vehicles, and then the results are added over all stations.

The required number of transit vehicles for 4 sub-problems for 1-hour and 2-hour evacuation operation horizons is illustrated in Table 3 and 4, respectively. The first column represents the problem instances by the percentage of transit-dependent people. Columns 2 through 6 summarize the results of the heuristic TABU search algorithm. Column 2 records the Time Elapsed (s) upon termination of the TABU search. Column 3 includes the evacuation time (ET) in minutes. Columns 4 and 5 record the actual number of saved evacuees (A_{saved}), and the planned number of saved evacuees (P_{saved}), respectively. The planned number of saved evacuees is equal to the total number of individual who arrive at stations during the evacuation planning horizon. The last column, column 6, indicates the required number of transit vehicles to evacuate the entire

population safely. The results reported for each problem are averaged over 10 problem instances.

Table 3

Required number of transit vehicles for 1-hour evacuation horizon

Problem	TABU Search					
	Transit Dep. (%)	Time Elapsed (s)	ET (min)	A _{saved}	P _{saved}	Required No. of Buses
5		211	62	435	435	13
10		292	62	832	832	21
15		327	62	1327	1327	31
20		400	62	1765	1765	40

Table 4

Required number of transit vehicles for 2-hour evacuation horizon

Problem	TABU Search					
	Transit Dep. (%)	Time Elapsed (s)	ET (min)	A _{saved}	P _{saved}	Required No. of Buses
5		1006	121	498	498	14
10		1154	122	1005	1005	24
15		1381	122	1547	1547	35
20		1555	122	2214	2214	47

The final stage in our numerical experiment is to integrate the optimization model into a simulation framework in which the credibility of PTRP is investigated. The involved theoretical challenges are twofold: first, it requires optimization modeling to develop a PTRP for a given evacuation operation horizon. Second, a simulation package

is utilized to simulate the urban transportation network, simulate different incident scenarios and implement the PTRP generated by using the optimization model. Our candidate simulation package is DYNASMART-P, which is classified as a mesoscopic traffic analysis tool.

Briefly stated, mesoscopic simulation models combine properties of both microscopic and macroscopic simulation models. Like microscopic models, the mesoscopic models' unit of traffic flow is the individual vehicle. Their movement, however, follows the approach of macroscopic models, depending on the average speed on the travel link. Although the mesoscopic models provide less accuracy than microscopic models, they work satisfactorily for planning purposes. In planning analysis, we are interested in the effect of various transportation planning alternatives in an aggregate level of vehicles rather than the individual vehicles.

DYNASMART-P is able to model the evolution of traffic flows in an aggregate level in a given planning horizon. Planning for special events, including evacuation scenarios, and for transit/bus routes is considered to be DYNASMART-P's potential application [10]. The unique application of DYNASMART-P is used to support our research project, which involves the utilization of transit vehicles to evacuate people in emergency situations.

To simulate a transportation network using DYNASMART-P, the required input data categories are network design data (including node, link and movement data), control data, demand data, scenario data and system data [22]. DYNASMART-P uses a custom-made utility, such as NETBUILDER, to read the network data from database files, such as TransCAD, and generate the corresponding input data. Although

NETBUILDER facilitates the process of building the transportation network, the volume of other required input data, such as control data and demand data, is still considerably high. Collecting the abovementioned data is out of the scope of this research project. Therefore, one of the existing traffic networks with calibrated traffic parameters is used as a proof of concept of the developed PTRP. The selected transportation network relates to the central part of the city of Fort Worth, Texas, which is illustrated in Figure 7.

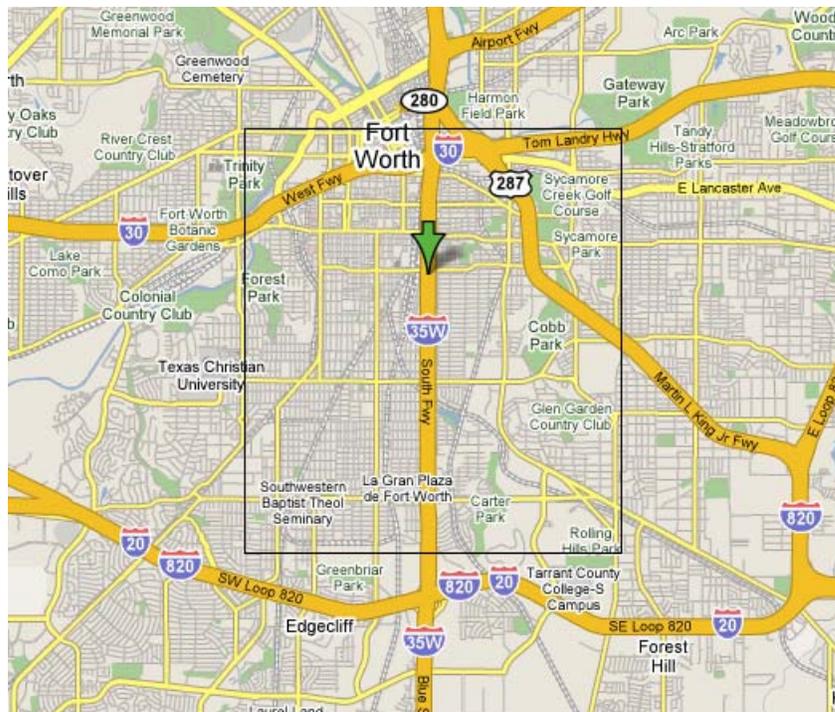


Figure 7

Map of the city of Fort Worth, TX

To simulate the transit system operational characteristics using DYNASMART-P, the required information includes the number of transit vehicles to be loaded, the start

time of operations, the transit vehicle routes, the dwell time, and the location of stations. The developed PTRP provides the abovementioned information. It is important to mention that the current version of DYNASMART-P considers identical dwell time at all stations, while the PTRP may result in varied dwell time. To conduct a fair comparison, first we set the dwell time to be 0 at all stations. After running the simulation, DYNASMART-P generates a *busTrajectory* output file, which provides the traffic information and itinerary associated with each transit vehicle. The *busTrajectory* output file reports the total travel time for each transit vehicle with 0 dwell time. The reported travel time is then added to the total dwell time calculated by the TABU search algorithm. The resulting travel time is compared with the evacuation time determined by the TABU search algorithm.

We select the first set of sub-problems related to the first base case with a 1-hour evacuation operation horizon for the numerical experiment at this stage. The percentage of the transit dependent residents is 5% and the number of available transit vehicles is 3, 5, and 10. The results are listed in Table 5. The first 2 columns identify the problem instance by the number of available transit vehicles and the vehicle number. Columns 3 through 6 summarize the results from the TABU search algorithm, and columns 7 and 8 summarize the results from the DYNASMART-P. Column 3 records the evacuation time (*ET*) in minutes. Columns 4, 5 and 6 include the travel time (*TT*) without dwell time (*DT*), the dwell time, and the travel time with dwell time. The travel time with dwell time is the summation of the travel time without dwell time and the dwell time. The travel time of transit vehicle with and without dwell time is recorded in columns 7 and 8, respectively. In order to report the travel time of transit vehicles with dwell time (column

8), the results in columns 5 and 7 are summed. The results reported for each problem are averaged over ten problem instances.

Table 5

TABU search vs. DYNASMART-P for the first sub-problem

Problem		TABU Search				DYNASMART-P	
No. of Buses	Bus ID	ET (min)	TT without DT (min)	DT (min)	TT with DT (min)	TT without DT (min)	TT with DT (min)
3	1	12	2	0	2	3	3
3	2	12	4	1	5	3	4
3	3	12	6	5	11	5	10
5	1	30	6	5	11	5	10
5	2	30	5	12	16	5	16
5	3	30	7	11	18	6	17
5	4	30	9	13	21	7	19
5	5	30	12	12	24	9	21
10	1	61	2	30	32	3	33
10	2	61	3	26	30	4	30
10	3	61	4	30	34	4	34
10	4	61	5	13	18	4	17
10	5	61	5	35	40	4	39
10	6	61	7	33	39	5	38
10	7	61	9	18	27	6	24
10	8	61	10	32	42	7	39
10	9	61	11	30	42	8	38
10	10	61	14	29	43	10	39

For the first problem instance with $\omega = 3$, the result from the DYNASMART-P indicates that the last transit vehicle reaches the safe location after 10 minutes, which is less than the evacuation time limit, 12 minutes, specified by TABU search algorithm. One can observe that a similar conclusion is also applicable for problem instances associated with $\omega = 5$ and $\omega = 10$. In addition the travel time calculated by TABU search is pretty close to that by DYNASMART-P. The results verify the capability of the model to respond to the dynamic nature of the traffic flow in emergency situations for the given evacuation operation horizon.

While the research focuses on the no-notice evacuation modeling and solution approaches, it is important to discuss the real-time computational effort and the required data for implementation purposes. Given the traffic network topology and the public transit system information of an urban area, the time-space transit network can be built before the occurrence of the incident. There are geographic information systems (GIS), such as TransCAD, designed specifically for use by transportation professionals to store, display, manage, and analyze transportation data. The number of evacuees shall be known *a priori* to be taken as the problem input as well. Demographic information can be used to determine the potential number of evacuees at the time of evacuation. Metropolitan planning organizations in urban areas provide comprehensive resources for this purpose.

The real-time traffic data used to be a major concern for researchers and practitioners involved in emergency evacuation planning. The emergence of ITS, which is used in most major US cities, however, has mitigated the difficulties in accessing the required traffic data. Nowadays, there are numerous sources that provide traffic

information that can be directly fed into the model. These sources may include but are not limited to stationary loops installed underneath highway pavements, GPS for truck fleets, or cellular phones for wireless carriers [5].

By modeling the problem, the remained issue is to solve the model efficiently at the time of the incident. As already discussed, the heuristic TABU search can be used to generate results that are comparable to that of CPLEX in a considerably shorter amount of time.

6. Conclusions and Remarks

The primary objective of this research is to improve the service level for transit-dependent citizens in emergency situations. We consider no-notice emergency situations, in which the location and the severity of the disaster are unknown ahead of time. In this situation, the transit system seems a reliable option for transit-dependent residents to get out of the danger zone. Based on the existing transit system, we develop a public transit routing plan (PTRP) model for an urban area to move residents from the danger zone to the safe location. This is the first time that the application of the public transit system is modeled analytically for no-notice evacuation purposes. The main assumption underlying the model is that the locations of station points and shelters are known *a priori*. The problem follows the structure of the network flow problem with additional side constraints. A mixed integer linear programming formulation is used to model the problem. The no-notice characteristics of the emergency situation necessitate a solution approach that generates the solution in a short amount of time. We proposed a heuristic

TABU search algorithm that demands significantly smaller computational effort compared to CPLEX to generate comparable results.

The proposed modeling approach has the capability to be used in real-time, no-notice evacuation scenarios. The required input data, including the traffic network topology, the demand distribution and the traffic density, are available using advanced systems such as GIS and ITS, which are deployed in most major urban areas.

A future extension to this research includes implementing the discussed optimization-simulation approach into an optimization-simulation feedback loop using a rolling horizon (RH) scheme. The conceptual structure of the optimization-simulation feedback loop is illustrated in Figure 8.

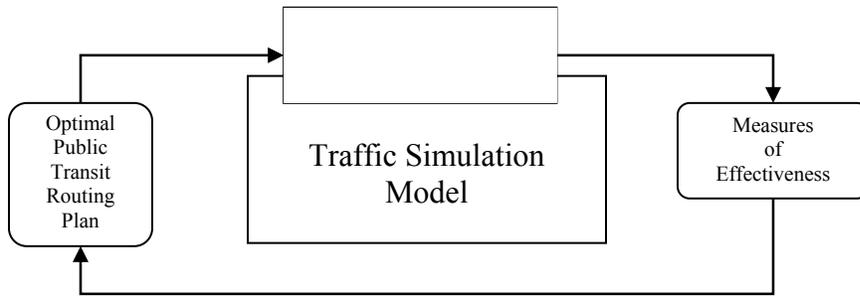


Figure 8

The conceptual structure of the optimization-simulation feedback loop

The underlying idea behind the RH approach is that current events are not influenced by events in the far future. This idea is integrated with our proposed

methodology in a way that the problem is solved for optimality for a relatively short time period called stage (γ). For a given stage, it is assumed that the complete information is available for the entire planning horizon through the duration of the stage. The public transit routing plan is solved for the entire stage but simulated only for the roll period (τ), where ($\tau < \gamma$). The entire time frame is rolled forward by the roll period, and the same process is repeated until the entire planning horizon is covered. The selection of the value of γ and τ involves the tradeoff between the computational effort and the solution quality. It is suggested to use the roll period of the order of 10 to 15 minutes, with the stage length of about 20 to 30 minutes for simulation experiments [23].

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