ABSTRACT

Title of Thesis:	LARGE-SCALE EVACUATION ROUTING AND SCHEDULING OPTIMIZATION WITH UNINTERRUPTED TRAFFIC FLOW
	Xuechi Zhang, Master of Science, 2014
Directed By:	Dr. Ali Haghani
	Department of Civil Engineering

In many emergency management operations, an efficient evacuation strategy is of great importance because if it is successful, it has the ability to significantly reduce the loss of property and human life. This thesis develops a routing and scheduling optimization framework for large-scale vehicular evacuation. To guarantee high optimization efficiency, we consider the routing and scheduling optimization as a two-stage problem instead of optimizing them as a whole (i.e. using time-space network). In the first phase, a multiple-objective binary programming model, with the objectives of minimizing the network clearance time and total in-network time is proposed to find an optimal routing plan. In the second phase, a simulation-based scheduling Heuristic is proposed to dynamically generate the time-dependent departure rates. A real-world evacuation scenario in Eastern Shore of Maryland is studied by using the proposed optimization model. The calculation results indicate a good optimization capability and flexibility of the proposed model.

LARGE-SCALE EVACUATION ROUTING AND SCHEDULING OPTIMIZATION WITH UNINTERRUPTED TRAFFIC FLOW

By

Xuechi Zhang

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Advisory Committee:

Professor Ali Haghani, Chair

Professor Paul Schonfeld

Professor Lei Zhang

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Dedication

To Dandan and my beloved parents

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Table of Contents

List of Tables

List of Figures

Chapter 1 : Introduction

1.1 Research Background

Potential hazards exist in people's daily lives every day. From the perspective of cause, hazards can be classified into two categories: manmade hazards and natural hazards. Manmade hazards are events like terrorist attacks, chemical leaks or explosions and nuclear leakage. Natural hazards are events like hurricanes, earthquakes, tsunamis and other naturally occurring disasters. However, there is no single hazard or disaster that exists absolutely independent from any other hazards or disasters. The inter-relationship among all kinds of hazards cannot be ignored in the emergency management process. For instance, a secondary disaster like a tsunami can occur following an earthquake, and a prescriptive terrorist attack can lead to a serious nuclear leakage. To prepare for these events, society should be alert and have a set of integrated operation plans to respond to these hazards. The core of emergency management operations is to protect human beings to the largest extent. People's safety shall always take the highest priority, which means evacuation operations in emergency situations to protect human safety are of the highest importance.

Due to high population density, urban areas are extremely vulnerable to the above-mentioned hazards. In other words, evacuation is more likely to occur in an urban area. In urban areas, designing efficient evacuation plans is the responsibility of emergency management agencies or authorities. However, the problem is not that easy to solve. The high density of evacuee population and the complexity of the urban transportation network can pose challenges. Various problems occur simultaneously when dealing with the large population and making use of the complex transportation network. Several critical questions regarding the urban evacuations are summarized below:

1) In the evacuation preparation stage, how should we assemble and manage a large number of evacuees to efficiently start the following evacuation?
2) Among the intricate urban roadways, which ones should be picked out for the special use of evacuation?
3) Should we mandatorily assign evacuation egress to the evacuees in an emergency situation?
4) Due to the large number of evacuees and limited roadway capacity, how do we come up with a staging evacuation strategy (i.e. loading the evacuees onto network in an optimal order)?
5) How do we control intersections so as to guarantee a smooth evacuation operation?

The aforementioned concerns show that evacuation planning for urban areas deserves more consideration than that in rural areas, due to high population density and intricate transportation systems. In the literature so far, seldom are there works directly dealing with the evacuation routing and scheduling planning inside an urbanized area with many of evacuation sources. The most critical problem for a large-scale urban evacuation is the intersection control and bottleneck identification. Actually, the intersection cannot be viewed as simply a network transshipment node. One reason is that the movements happening inside an intersection have multiple constraints. Another important reason is that a turn movement inside an intersection always has a relatively low travelling speed in comparison with the travelling speed in a general roadway link. As a consequence, the bottleneck is more likely to occur at an intersection due the low speed of turn movements. The research detailed in this paper uses these considerations to propose a realistic and efficient evacuation operation framework specifically in an urbanized area.

1.2 Research Objectives and Scope of Work

This study aims to deal with a large-scale vehicle-based evacuation routing and scheduling optimization for a large population density. Due to the significance of prescriptive evacuation planning, there are abundant advanced techniques emerging these years. To avoid redundant efforts, a comprehensive literature review on the vehicular evacuation has been conducted.

Based on the historical works in the literature, two research goals are set and fulfilled. Specifically, an evacuation routing optimization model and a network-loading algorithm are proposed separately to better assist the emergency decision maker to manage the overall evacuation process. Instead of optimizing the routing and scheduling as a whole by making use of a time-space network, this research calculates the routing and scheduling decision variables separately. This is mainly because a complex network with a large evacuation demand makes it nearly impossible to acknowledge the optimal network clearance time, which is essential to expand an evacuation network along a discrete time horizon. In addition, the solution calculation of a time-space network is extremely time-consuming. Consequently, this type of model is rarely used in reality.

To achieve the first goal (i.e. routing optimization), a bi-level binary programming model with multiple objective functions is formulated. The objectives of this model are to minimize both the network clearance time and the total in-network time, which consists of route traverse time and average network loading delay. To better guarantee the evacuation process is smooth and effective, intersection movement conflicts are eliminated during the optimization process. In other words, the optimization process is conducted by constructing a set of uninterrupted traffic flows. Meanwhile, the evacuation bottleneck for each evacuation path is identified during the optimization process. To achieve the second goal, a simulation-based scheduling heuristic (i.e. discharging algorithm) is proposed. A mesoscopic traffic simulator is implemented and incorporated in this algorithm so as to feedback the real-time traffic state to the heuristic. Two case studies are used to conduct the calculation experiments, one is based on a fabricated urban grid network, and the second one is based on a real-world evacuation scenario from the Eastern Shore of Maryland.

1.3 Thesis Organization

Subsequent chapters of this thesis are organized as follows. In Chapter 2, a literature review is provided. To better understand the related literatures, the review work further classifies the current techniques based on three levels. They are, macroscopic methodology, mesoscopic methodology and microscopic methodology. Chapter 3 describes the development of the aforementioned evacuation routing optimization model. A specific solution approach is developed and illustrated at the end of this chapter. In Chapter 4, to come up with an optimal demand discharging strategy, a simulation-based evacuation heuristic is developed and discussed. Chapter 5 conducts several case studies to test the proposed optimization framework, and the experiment results are summarized and discussed. Finally, Chapter 6 concludes the overall work and provides some future work directions.

Chapter 2 : Literature Review

Evacuations happen in various kinds of emergency situations, like a fire in a building, a terrorist attack, or a large-scale hurricane. In terms of applications, evacuation research can be further divided into two main tracks. One is pedestrian-specific evacuation, and the other one is vehicle-based evacuation. This work specifically deals with evacuation optimization in terms of vehicle-based scenarios. Thus, the literature review here mainly focuses on the current techniques belonging to this track. Some detailed literatures on pedestrian-based evacuations can be found in the works of Schreckenberg and Som (2002), Kuligowski and Richard (2005), and Helbing and Anders (2009). To investigate and understand the abundant literature in a well-organized manner, the review work here further classifies the vehicle based evacuation techniques into three categories. They are evacuation planning techniques by a macroscopic approach, a mesoscopic approach and a microscopic approach, respectively. In addition to the related techniques, the advantages and drawbacks of each category of approaches is also discussed at the end of each subsection.

2.1 Macroscopic Approaches

Macroscopic approaches are mainly used to approximately estimate the lower bounds for the evacuation time, like network clearance time and total evacuation time (Hamacher and Stevanus, 2002). Models belonging to this type of approach do not consider any individual behaviors during the evacuation process. Instead, they always model the whole situation as flow transmission and evolution process. The main way to deal with this flow-optimization problem is based on the work of Ford and Fulkerson (1958), in which a maximal amount of flow has to be sent from a source node to a sink node in a given time of period. This optimization concept can be explicitly extended to a vehicle-based evacuation scenario by letting the source node be the assembly point of evacuees and letting the sink node be the safety exit. Yamada (1996) proposes a network flow approach to a city emergency evacuation planning. In his model, evacuation sources and safety points are predefined in a given urban transportation network. Then the optimization is conducted based on a shortest path problem and a maximal flow and minimal cost problem. Prescriptive evacuation routes and lower bounds of evacuation time are outputs of his model. However, due to the absence of a real-world simulation study, the lower bound is not validated. Cova and Justin (2003) formulate the evacuation process as a lane-based mixed-integer programming problem with the objective of minimizing total evacuation distance. This model first distinguishes the vehicle-based evacuation problem with other flow-based evacuation problems in history. That is, the traffic conflict within intersections is very important. Obviously, an intersection cannot simply be viewed as a transshipment node in the evacuation network. The turn movements conflict and intersection capacity play a significant role during the evacuation process. Thus, Cova and Justin (2003) incorporate the conflict elimination constraints in their linear model, which is specifically used for a vehicle-based evacuation scenario in an urban area. In addition, a simulation model according to HCM is built to validate the model's outputs. Kim et al. (2007) present the first macroscopic approach for finding a contraflow network reconfiguration to minimize the evacuation time. These concepts dramatically enlarge the solution search space. Thus, they propose a greedy algorithm to produce a satisfied solution. Using the same concepts as Kim et al. (2007), Xie et al. (2010) come up with a bi-level optimization model in which lane reversal and conflict elimination are optimized to assist the dynamic traffic assignment optimization.

The cell transmission model (CTM)-based evacuation planning optimization is also classified as a macroscopic approach. Although CTM-based optimization models make the evacuation evolution more accurate, it still does not incorporate the inter-relationship between each evacuee. In other words, it is still a kind of network flow optimization problem but with a higher network resolution. Based on CTM, Ziliaskopoulos (2000) proposes a linear programming model for optimum dynamic traffic assignment problem (DTA). DTA can be extended to an evacuation problem just by substituting OD pair information with sources and sinks information. Liu et al (2006) proposed a revised CTM-based optimization model with two-level objectives, one is to maximize the throughput and the other one it to minimize the total evacuation time. In addition, Liu et al. (2007) built an evacuation specific optimization model on the foundation of Ziliaskopoulos (2000)'s linear programming model. However, due to the huge amounts of decision variables, Liu et al. (2007) did not directly calculate their model. Instead, two heuristic models are proposed to find a satisfied solution. It partially reflects that the CTM-based evacuation model is not practical for a large-scale evacuation scenario (i.e. evacuation in an urbanized area). Some other CTM-based evacuation optimization models are Liu et al. (2006) and Kalafatas and Peeta (2009). In the work of Kalafatas and Peeta (2009), lane reversal concepts are also used to augment the roadway capacity. Moreover, based on the concept of CTM, Zhang and Chang (2011) developed a Cellular Automata-based model for simulating vehicular-pedestrian mixed flows in a congested network. Then they applied this mixed flow concept into evacuation and proposed an integrated linear model for the design of optimized flow plans for massive mixed pedestrian-vehicle flows within an evacuation zone (Zhang and Chang (2013)).

In addition, the geographical information system (GIS) has gradually become an important part in evacuation optimization and management because of its excellent capacity of processing big data and a more intuitional visualization. Church and Cova (2000) first proposed a GIS-based optimization model that identifies small areas or neighborhoods with a high ratio of population of exit capacity in terms of an evacuation network. Although their model does not explicitly generate the egress routing and scheduling information, it is of great significance to prioritize the evacuation schedule during a staged evacuation process. Similarly, Chen et al. (2009) came up with an evacuation risk assessment model while considering pre- and post-disaster factors. As for the evacuation routing optimization with GIS system, Saadatsereshit et al. (2009) develop multi-objective evolutionary algorithms with the goal of optimally distributing the population into the safe areas. Ye et al. (2012) conducted spatial analysis for mapping evacuee demand distribution with the constraints of shelter space accessibility in an earthquake scenario. These GIS-based evacuation routing models do not explicitly deal with specific dynamic traffic control during an urban evacuation, but they can efficiently assist the evacuation management agency to manage the whole evacuation from a macroscopic view.

2.2 Microscopic Approaches

Optimization models from microscopic views are mostly simulation-based since it is difficult to capture all network operational constraints and driver responses fully with mathematical formulations. For instance, Chen et al. (2007) investigated impact of different signal timing plans for urban evacuation by using arterial corridors. Zou et al. (2005) developed a simulation-based framework for the Ocean City area (Maryland) and investigated the efficiency of six given evacuation plans. Similar work has been done in the work of Liu et al. (2005). Meanwhile there are also some analytical models aiming to optimally solve the vehicle-based evacuation planning. For example, when considering interplay among all evacuation vehicles, Chien and Vivek (2007) explicitly formulated the evacuation time as the summation of waiting delay and traverse time for a single street evacuation situation. Then, a classical mathematical optimization method is used to find the optimal solution. However, this type of method is not practical, especially for a large-scale evacuation scenario. Since the number of decision variables is huge, it is impossible to directly solve the analytic equation for an optimal solution. After 1999's Hurricane Floyd evacuation in costal South California, Dow and Susan (2002) conducted a survey to investigate the relationships between evacuation issues (i.e. evacuation time, evacuation distance and evacuation method) and people's decisions. They concluded that transportation issues are of huge significance during an evacuation process, as they not only impede people's evacuation but also influence people's final decision in microscopic way. With this type of consideration, Chen et al. (2006) built a microscopic simulation model to investigate the network clearance time in the Florida Keys when it comes to a hurricane landfall. Questions like the number of people who will be stranded if the evacuation routes are impassible during a particular scenario are answered. At the same time, Chen and Franklin (2006) also take advantage of their agent-based microscopic simulation model to analyze the efficiency of simultaneous and staging evacuation strategies, respectively. A key conclusion is that staging evacuation strategy has a better performance in an urban evacuation scenario. In considering the impact of human's behavior on the evacuation time estimates (ETEs), Lindell and Carla (2007) investigate the principal behavioral variables that affect hurricane ETEs. The critical behavioral assumptions further enrich the evacuation analysis in a microscopic view. Lindell (2008) studies the human behavior in an emergency situation and proposes a comprehensive human behavior-forecasting model. Based on that, an empirically based large-scale evacuation time estimate mode (EMBLEM2) is built while taking the evacuee's behavior into consideration. Different from the macroscopic models, human preparation time during an evacuation is also considered as part of the overall evacuation time.

A comprehensive review on travel behavior modeling in dynamic traffic simulation models for evacuation can be found in Pel et al. (2012).

Some other literature in which microscopic simulation technique is used to plan an evacuation are briefly summarized as follows. Jha et al. (2004) developed a microscopic simulation model (MITSIMLab) for evaluating evacuation plans for the Los Alamos National Laboratory (LANL). The scenarios adopted include full or partial closures of various roadways, limited access to some special facilities and security delays at certain locations. The evolution dynamics of the evacuation process is captured and analyzed in detail. Liu et al. (2007) proposed to use a microscopic traffic simulation model to implement the short-term traffic control strategy in order to dynamically guide the evacuation traffic flow. Lämmel et al. (2008) developed a simulation model based on the MATSim framework to generate an optimal evacuation traffic assignment (i.e. Nash equilibrium). Agent dynamics based on a FIFO queue model are incorporated in their model. This agent-based simulation model provides plausible results regarding the predicted evacuation time and bottlenecks.

2.3 Mesoscopic Approaches

Macroscopic models only have the capability of roughly estimating the evacuation time. As a result, the corresponding optimal routing and scheduling guidance are generated in ideal conditions and by relying on too many assumptions. While evacuation planning in a microscopic way indeed provides more realistic details during the whole process, simulating a single particular plan will take a huge amount of calculation time, let alone for millions of optional plans. In considering the performance gap between these two methodologies, a mesoscopic approach in dealing with evacuation optimization becomes more and more popular. Jain and Smith (1997) first proposed a vehicular traffic flow model based on M/G/C/C state-dependent queuing models. With this queuing model, the congestion of traffic flow with Markovian arrivals on a single road link can be statistically captured. This model is first taken into the evacuation optimization in the work of Stepanov and Smith (2009), in which an integer programming model is proposed to minimize the average travel distance and network clearance time. Their model provides congestion probability on each roadway link, which can be pre-limited within an upper bound. However, only routing guidance is provided using this model. When it comes to an evacuation scenario with a huge population, scheduling guidance is of extremely significance because we cannot simultaneously load all of the demand into the transportation network. In addition, Stepanov and Smith (2009) do not provide flow-control strategies within an intersection. From the perspectives of eliminating movement conflicts at an intersection, Bretschneider and Kimms (2011) develop a mixed-integer programming model to optimize the routing and scheduling problem by using a time-expanded network approach.) Although they name their model as a basic mathematical flow optimization framework, traffic dynamics with lane-based resolution are integrated. Thus, this model is also classified as a mesoscopic approach. Due to the high calculation complexity of a time-expanded network, a heuristic is also proposed in their work to generate satisfactory solutions. However, the main drawback of a time-expanded network optimization is that a proper time horizon must be given at the beginning. In real world scenarios, this time horizon is difficult to estimate, especially for a problem with large demand. If the time horizon is estimated below the value of the optimal condition, no feasible solution can be found; if it is overestimated, the output we get is just a sub-optimal solution. Therefore, a time-expanded network is only suitable to a small size problem.

Another practical way of mesoscopic optimization is discrete simulation-based optimization. As is shown in Figure 2-1, this type of optimization method takes advantage of a discrete traffic simulator together with a set of Heuristics to dynamically assign and load the evacuation demand to the transportation network. Sbayti and Mahmassani (2006) make use of a successive average-based iterative heuristic to determine the departure times for an evacuation process in consideration of the influence of background traffic. A traffic simulator called DYNASMART-P is used to propagate the vehicles on their prescribed paths and determine the state of the system. At the end of the discrete simulation, a time-dependent staging evacuation policy is generated for each selected origin. Afshar and Haghani (2008) developed a comprehensive heuristic framework for dynamic evacuation with the Spread-Squeeze concept. In their framework, a set of spread methods and a set of squeeze methods are proposed separately. This gives the flexibility of the application of these Spread-Squeeze heuristics to different size evacuation scenarios. Although Afshar and Haghani (2008) do not explicitly consider the routing determination process, their optimization framework can be extended to a routing and scheduling optimization framework with the introduction of some dynamic routing algorithms.

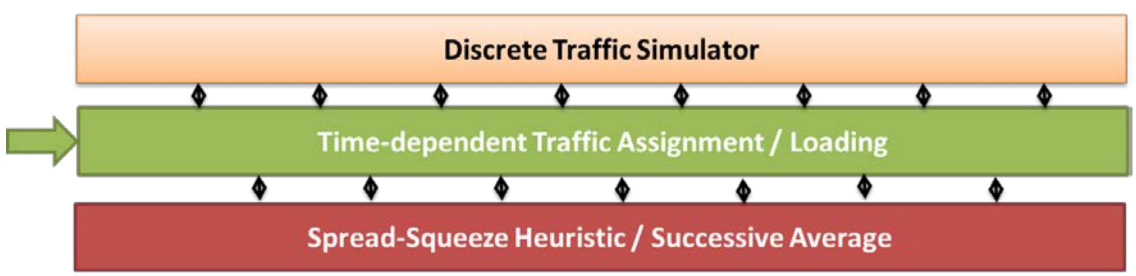


Figure 2-1: Flow Chart of Discrete Simulation based Optimization

In this research, the evacuation optimization is considered a two-level problem (i.e. routing and scheduling). In the upper level, a routing optimization model is formulated as a binary integer programming problem with the objective to minimize the total evacuation time. During the routing optimization process, intersection conflicts are eliminated and the uninterrupted evacuation flow paths are generated. In the lower level, with the input of the prescriptive egress routes, a greedy algorithm based on a discrete traffic simulator is proposed to dynamically determine the time-dependent departure rate for each source.

Chapter 3 : Routing Optimization Model

3.1 Mathematical Network Representation

The real world transportation network is abstractly represented by a directed graph *G (N, A)* with node set *N* and arc set *A*. In this model, every intersection of the evacuation network is replaced by a set of intersection nodes (As is shown in Figure 3-1and Figure 3-2). The decomposition of an intersection aims to further model the movement conflicts within an intersection. Thus, node set *N* consists of four types of nodes: source nodes, transshipment nodes, sink nodes as well as a dummy node connecting every sink. The travel time and capacity on any arc connecting the real destination node and the dummy node are set to 0 and infinity, respectively. In a real world scenario, a source node might be any evacuation assembly point, like exit point of a specific district block, or entrance ramp of a freeway. Sink nodes can be shelters or exits of a particular hazard area. Transshipment nodes usually denote intersections or some specific roadway inner points. Sometimes a source node or a sink node can also function as a transshipment node. Arc set *A* consists of all the directed arcs connecting nodes in *N*.

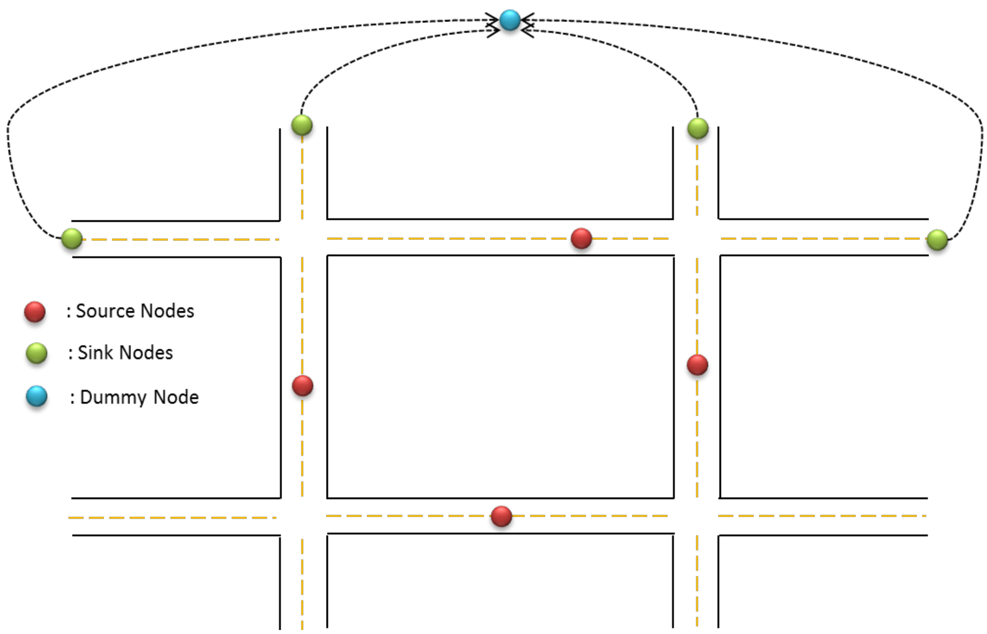


Figure 3-1: An Example of a Real-world Evacuation Network

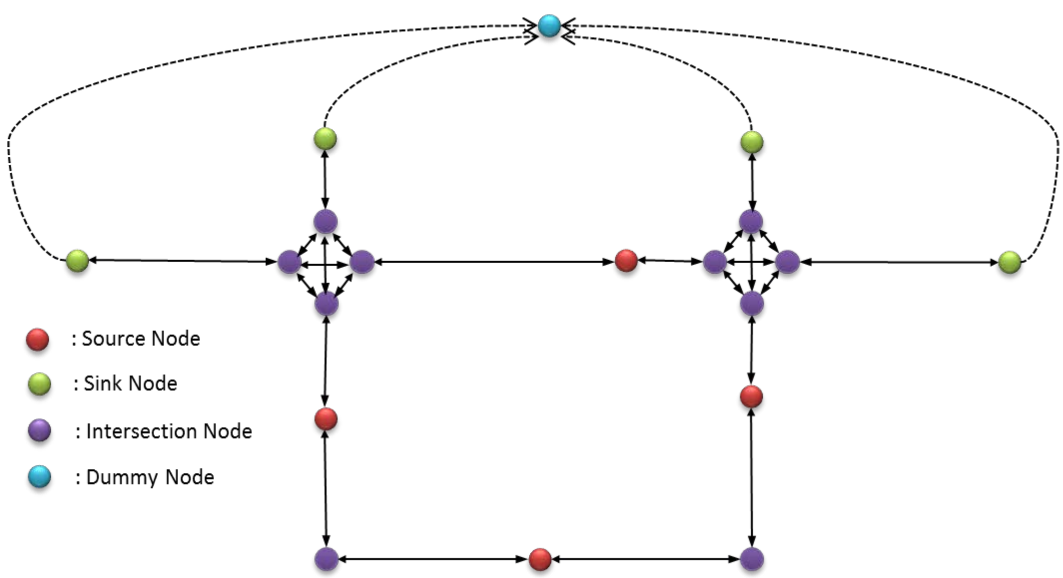


Figure 3-2: Corresponding Network Representation Graph of the Example in Figure 3-1

To facilitate the representation of movement conflicts within an intersection, a two-indices based node notation is used here. The detailed demonstration of this type of network element notation is illustrated in the work of Bretschneider and Alf Kimms (2011). For this type of notation, any node is labeled with a unique number pair *(i,m)*. The first index *i* usually classifies a set of nodes with common properties or sharing a common intersection. For example, all nodes adjacent to intersection *i* can be labeled as *(i,m)*, which indicates this is the mth node within intersection *i*. Thus, a directed arc can be labeled as *[(i,m),(j,n)]*, which represents the arc from node *(i,m)* to node *(j,n)*. In addition, to facilitate the conflicts modeling within an intersection *i*, we assume the nodes are incrementally labeled clockwise within an intersection (see Figure 3-3 and Figure 3-4). Here, a two-indices based node notation is used.

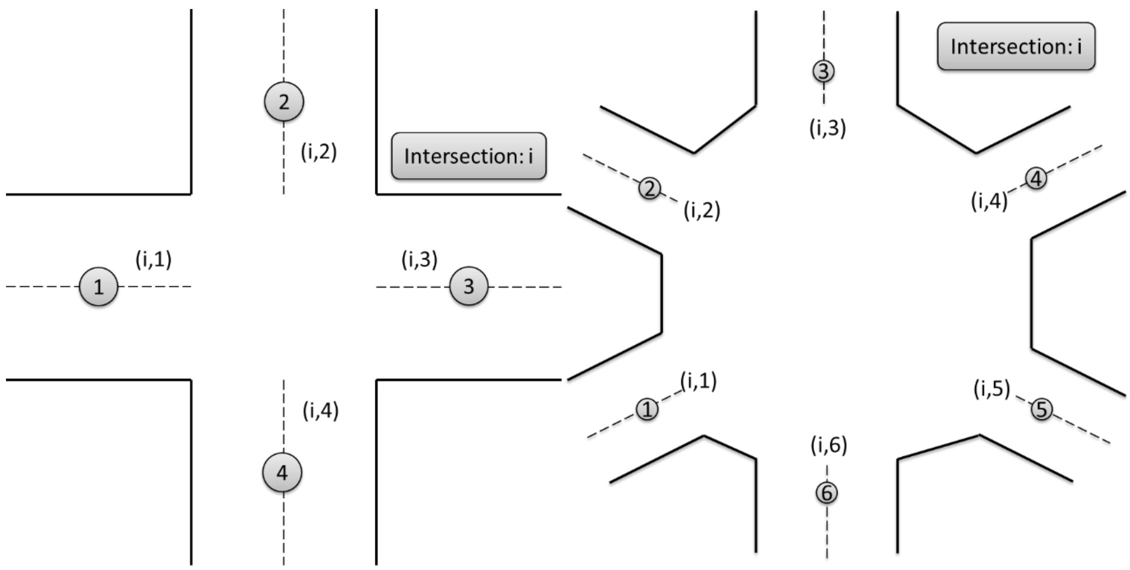


Figure 3-3: Node labelling illustration on a 4-leg intersection (left) and a 6-leg intersection (right)

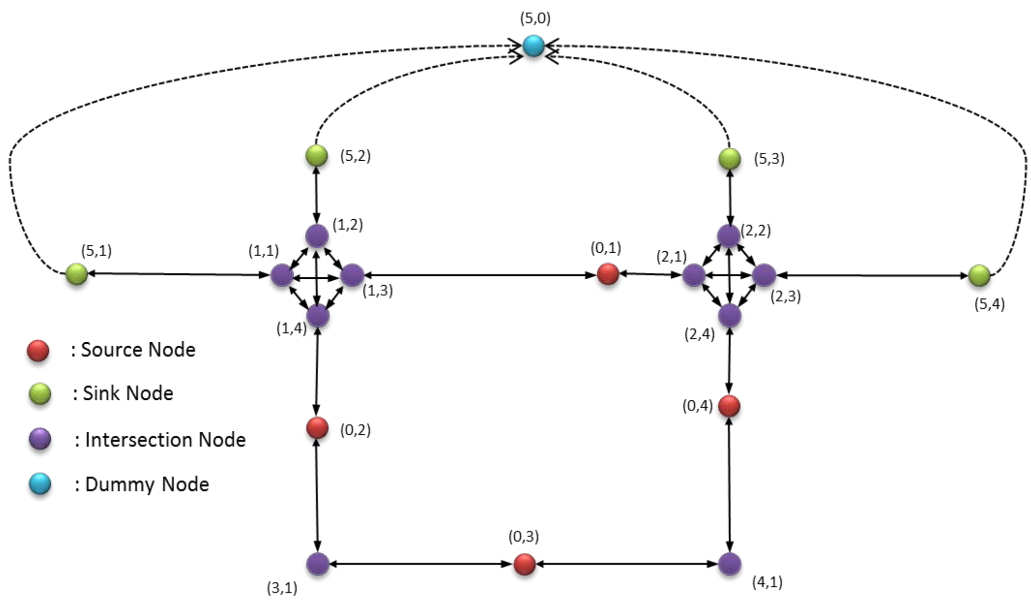


Figure 3-4: Label each node with a unique two-indices based ID

3.2 Notations

Network elements,

N_s, *set of evacuation source nodes*

N_t, *set of transshipment nodes*

N_d, *set of evacuation sink nodes*

N_0, *dummy nodes connecting every real sink node*

$N = N_s \cup N_t \cup N_d \cup N_0$, *set of network nodes*

A_s, *set of general roadway arcs*

A_n, *set of arcs inside intersections*

A_0, *set of arcs* connecting real sink nodes and the dummy nodes

$A = A_s \cup A_n \cup A_0, \qquad set\ of\ network\ arcs$

$(i, m),$

$index\ of\ a\ network\ node, where \begin{cases} i > 0, & node\ (i,m)\ belongs\ to\ intersection\ i \\ & i = 0,\ \ otherwise \end{cases}$

$[(i, m), (\mathrm{j}, \mathrm{n})],$ directed arc from node $(i, m)\ to\ node\ (\mathrm{j}, \mathrm{n})$

Traffic parameters,

$c_{[(i,m),(\mathrm{j},\mathrm{n})]}, \qquad capacity\ of\ arc\ [(i, m), (\mathrm{j}, \mathrm{n})], measured\ in\ veh/min$

$t_{[(i,m),(\mathrm{j},\mathrm{n})]}, \qquad expected\ travel\ time\ on\ arc\ [(i, m), (\mathrm{j}, \mathrm{n})], measured\ in\ min$

$D_{(0,k)}, \qquad demand\ of\ evacuees\ in\ origin\ (0, k), where\ (0, k) \in N_s$

$\theta_i, \qquad degree\ of\ intersection\ i$

$L_{[(i,m),(i,n)]}, \qquad set\ of\ intersection\ leg\ indices\ at\ the\ lefthand\ side\ of\ arc\ [(i, m), (i, n)],$

where $L_{[(i,m),(i,n)]} = \{m\ mod\theta_i + 1, \cdots, \theta_i - ((\theta_i - n + 1)mod\theta_i)\}$

$R_{[(i,m),(i,n)]},$

$set\ of\ intersection\ leg\ indices\ at\ the\ righthand\ side\ of\ arc\ [(i, m), (i, n)],$

where $R_{[(i,m),(i,n)]} = L_{[(i,n),(i,m)]}$

$M, \qquad a\ preset\ large\ number, i.e. M\ is\ set\ greater\ than\ total\ number\ of\ source\ nodes$

Decision variables

$$\alpha^{(0,k)}_{[(i,m),(\mathrm{j},\mathrm{n})]} \begin{cases} 1, & arc\ [(i,m),(\mathrm{j},\mathrm{n})]\ is\ used\ by\ source\ (0,k) \\ 0, & otherwise \end{cases}$$

$$\gamma_{[(i,m),(i,n)]} \begin{cases} 1, & arc\ [(i,m),(i,n)]\ within\ intersection\ i\ is\ picked\ up\ in\ the\ routing\ plan \\ 0, & otherwise \end{cases}$$

3.3 Model Formulation

3.3.1 <u>Network Clearance Time</u>

Network clearance time is the time duration to evacuate the overall evacuees out of the emergency region. This measurement indicator is of great significance in evacuation planning, since the evolution of a disaster is always exponential and we need to evacuate the people to some safety areas as fast as we can. A more general definition of network clearance time is time difference between the time point at which the last evacuee gets out of the evacuation region and the time point at which the evacuation process starts. However, when the evacuation demand is relatively large (i.e. the overall demand cannot be loaded into the network at once or simultaneously), it is very hard to calculate the time point at which the last evacuee (e.g. vehicle) is able to get out of the emergency region (i.e. reaching its safety destination). Therefore, we need to find some quantifying techniques to approximate the network clearance time when the evacuation demand is large so as to set the minimization of this indicator as the optimization objective. Given a set of equilibrium evacuation flow upon an evacuation network, we define the network's bottleneck as the link which has the largest ratio of its total serving demand and its capacity. In our case, the bottleneck arc $[(i,m),(j,n)]^*$ can be figured out by calculating the following maximum equation.

$$\mu^{*} = \max\{\sum\nolimits_{\forall(0,k)} \frac{D(0,k)\cdot\alpha_{[(i,m),(\mathrm{j,n})]}^{(0,k)}}{c_{[(i,m),(\mathrm{j,n})]}} | \forall \text{ arc } [(\mathrm{i,m}),(\mathrm{j,n})] \in \mathrm{A}\} \tag{3.1}$$

This term is based on the concept of reserve capacity, which is always used in dealing with uncertain traffic demand problems (Yang and Michael, 1997). In addition, Hua et al (2013). named this numerical value as the link overload degree in their evacuation modeling and argued that the value of the maximal link overload degree in a network is of high correlation with the value of the network clearance time. Suppose that there is no intersection waiting delay (i.e. signal timing or stop-and-go traffic control) during an evacuation, which means the overall evacuation flow moves in a smooth way, then this term μ^{*} can be viewed as a good lower bound of the network clearance time. Actually, most of the evacuation delays in a real world scenario is caused by the stop-and-go control delays, such as signal timing stops at intersections, and stop sign controls ("*Regional Evacuation Modeling in the United States: A State of the Art Review*"). To make the evacuation process more efficient, evacuation researchers have put more and more attention to the intersection conflicts elimination when it comes to a large scale evacuation process. Cova and Justin (2003) firstly introduced the lane-based evacuation optimization model as well as the intersection conflicts elimination strategies, which proved to be very efficient in large demand evacuation, especially in an urban area. Bretschneider and Kimms (2011) developed a basic mathematical optimization model with objective of minimizing the weighted total evacuation time, where the elimination of the intersection conflicts is considered as a key part in the optimization model. Liu et al. (2012) developed a bi-level optimization model aiming to enhance the evacuation efficiency by constructing uninterrupted traffic flows in some intersections. Therefore, using the so-called link overload degree as an approximation of the network clearance time is reasonable, especially in the case of our model (i.e. constructing a set of smooth/uninterrupted evacuation flows).

3.3.2 <u>Total Travel Time</u>

Travel time of a particular evacuee during an evacuation is defined as the time period it takes to travel out of the emergency region. In other words, the travel time of an evacuee is calculated as the time difference between its network-loading time point and the safety-arrival time point. This term can be further described by the following equation with the aforementioned notations,

$$\mathrm{T}_{\text{traverse}}(r) = \sum_{[(i,m),(\mathrm{j,n})]\in r} t_{[(i,m),(\mathrm{j,n})]} \tag{3.2}$$

Where $\mathrm{T}_{\text{traverse}}(r)$ denotes the traveling time of route r. Here it is simply the summation of the travel time of each roadway segments that is covered in route r. This is also called leadtime in some network flow problems (Lin, Yi-Kuei, 2003). With the route travel time calculated this way, the total travel time during an evacuation can be derived as,

$$TT = \sum_{(0,k)\in N_s} D_{(0,k)} \cdot \sum_{[(i,m),(\mathrm{j,n})]\in A}\left[\alpha^{(0,k)}_{[(i,m),(\mathrm{j,n})]} \cdot t_{[(i,m),(\mathrm{j,n})]}\right] \tag{3.3}$$

Where $D_{(0,k)}$ is the evacuation demand of source (0,k), and the inner summation $\sum_{[(i,m),(\mathrm{j,n})]\in A}\left[\alpha^{(0,k)}_{[(i,m),(\mathrm{j,n})]} \cdot t_{[(i,m),(\mathrm{j,n})]}\right]$ associates the route evacuation time with decision variable $\alpha^{(0,k)}_{[(i,m),(\mathrm{j,n})]}$.

The total travel time is always a significant performance measure in traffic assignment problem, where the objective is minimizing the total travel time among the overall demand to reach a system optimal condition. However, the link travel time $t_{[(i,m),(\mathrm{j,n})]}$ is usually of high variance and cannot be deemed as a constant in the general traffic assignment problem since the traffic control level is relatively low (i.e. the traffic demand is always loaded into the network simultaneously and every single vehicle is thought to be greedy). But the evacuation operation is quite different with the case in general traffic assignment problems. Due to the large evacuation demand and limited egress, the traffic managers or operation authorities always take a high level of traffic control during the evacuation process in order to avoid the “traffic explosion”. In other words, to provide the maximal network throughput per time unit, the emergency authorities always expect the evacuation flow travels exactly at the capacity of the roadway segments in the planning stage. Hence, it is realistic to fix the link travel time as its capacity travel time when we are planning an evacuation, and this is always the case in the evacuation research literature.

3.3.3 Total In-Network Time

Here we define another time measure of an evacuation process, i.e. total in-network time. Just as it literally indicates, the in-network time of a specific evacuee is the total duration it takes to get out the emergency area or reach to its safety destination since the evacuation process starts. Different with the definition of the travel time in the above paragraph, the in-network time of a specific evacuee additionally includes the preparation time and loading waiting delay for this evacuee to get into its egress route at its source. As is illustrated in Figure 3-5, the total in-network time is exactly the integral of the non-arrival demand curve in terms of the evacuation duration. Suppose that every evacuee is able to load into the network in a very short time period (i.e. ignore the preparation stage). It is noted that when the evacuation demand is relatively small against the evacuation network, in which case all of the evacuees can start their evacuation simultaneously, there is no waiting delay for loading resulting from the limited network capacity. Hence, the total in-network time will be equal to the total travel time discussed in the previous paragraph. However, this is not always the case in the real-world large-scale evacuation scenario, where the evacuation demand is large and the network capacity is very limited (Chen. et. at. 2006 and Chien. et al. 2007). Thus, a stage based evacuation strategy must be taken, and the waiting delay no longer can be ignored (like the case of Liu et al. 2006). In many real-world cases, the waiting delay of a particular evacuee is even several times of its in-network travel time to its destination.

Total In-Network Time

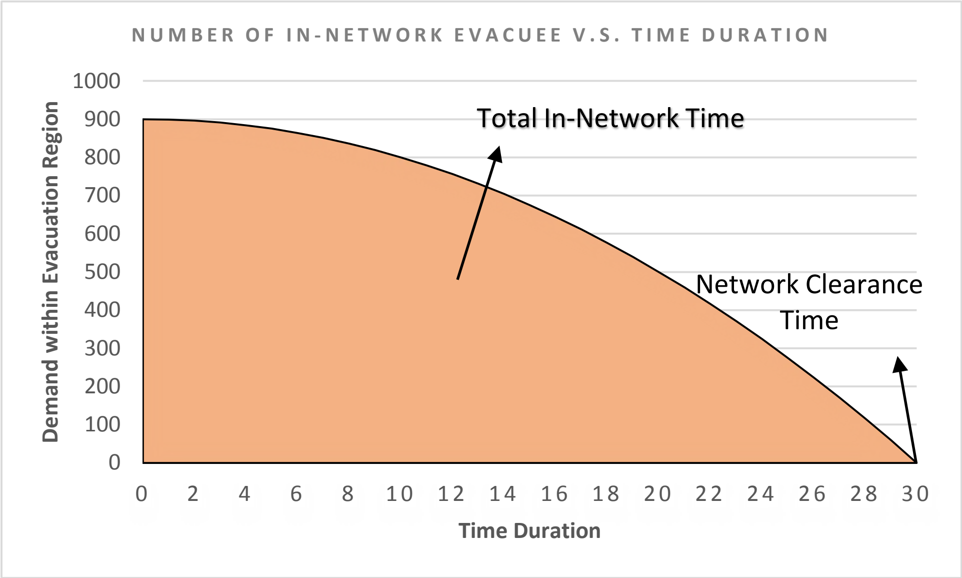


Figure 3-5: Representation of total in-network time and network clearance time with respect to a general evacuation curve

In our basic mathematical model, we assume the preparation time of each evacuee can be ignored in comparison with the average loading waiting delay and the evacuation traveling time. Therefore, the total in-network time can be analytically derived as two parts, one is the loading waiting delay and the other one is the total evacuation traveling time. The calculation of total evacuation traveling time can just be achieved by using equation (3.3). Here we only need to derive the formula to calculate the total loading waiting delay.

From the perspective of basic network flow problem, the average loading waiting delay of a specific source is determined (or constrained) by the bottleneck capacity on its egress route. We further assume the serving time of an arc can be approximately equal to the ratio of its accumulative demand and its capacity (as is calculated in equation 3.4). This is also referred as the reserve capacity of a network link, which is always used in uncertain traffic demand assignment problem (Hai et al. 1997)

$$T_{serve}([(i,m),(\mathrm{j},\mathrm{n})]) = \frac{\sum_{(0,k)\in N_s} D_{(0,k)}\cdot \alpha_{[(i,m),(\mathrm{j},\mathrm{n})]}^{(0,k)}}{c_{[(i,m),(\mathrm{j},\mathrm{n})]}} \tag{3.4}$$

This physical meaning of term is not difficult to understand. It is just the time duration that roadway segment [*(i,m), (j,n)*] is consistently used by a set of traverse demand $\sum_{(0,k)\in N_s} D_{(0,k)} \cdot \alpha_{[(i,m),(\mathrm{j},\mathrm{n})]}^{(0,k)}$. For a real-world scenario with uninterrupted evacuation traffic flows, this formula is valid and can be directly used to identify the route bottleneck. This is because for an uninterrupted evacuation flow scenario every roadway link is consistently serving its traffic demand. In other words, a serving gap between two groups of arrival demand does not exist. Moreover, this concept can also be applied to a scenario with interrupted traffic flows (e.g. traffic conflicts at an intersection), and only some adjustments need to be made at these conflict points. For instance, at an intersection with signal timing control to avoid two movement conflicts (e.g. northbound traffic versus westbound traffic), we can divide and allocate the intersection capacity to these two traffic routes according to the signal timing ratio. Hence we can conceptually assume that each arc is still consistently serving its arrival demands during the whole evacuation process. Therefore, the average waiting delay (e.g. minute/veh) for a source with egress route *r* can be derived as:

$$E[TW(r)\} = \frac{1}{2} \cdot \max\{\sum_{(0,k)\in N_s} D_{(0,k)} \cdot \alpha_{[(i,m),(\mathrm{j},\mathrm{n})]}^{(0,k)} \cdot \frac{1}{c_{[(i,m),(\mathrm{j},\mathrm{n})]}} |\forall[(i,m),(\mathrm{j},\mathrm{n})] \in r\} \tag{3.5}$$

Equation (3.5) can be further interpreted as, if an evacuee (e.g. vehicle) is going to traverse route *r* to reach its safety destination, then $E[TW(r)\}$ gives the expected value that how long should this evacuee wait to get loaded onto this route. This expected estimation is valid based on two assumptions:

(1) The linear relationship between the link serving time and its arrival demand (i.e. the capacity of each link is unchanged);

(2) Each roadway link is consistently serving its arrival demand during the evacuation process (i.e. uninterrupted evacuation flow, at most merge and diverge are accepted).

Finally, by combining the expected total loading waiting delay and the total evacuation traveling time, the total in-network time for an evacuation process can be calculated as equation (3.6).

$$\mathrm{T}_{\mathrm{in-net}} = \sum_{(0,k)\in N_S} D_{(0,k)} \cdot E[\mathrm{TW}_{(0,\mathrm{k})}] + \sum_{(0,k)\in N_S} D_{(0,k)} \cdot \sum_{[(i,m),(\mathrm{j,n})]\in A} [\alpha^{(0,k)}_{[(i,m),(\mathrm{j,n})]} \cdot t_{[(i,m),(\mathrm{j,n})]}] \tag{3.6}$$

Where, $E[TW_{(0,k)}] = \frac{1}{2} \cdot$

$\max\left\{\alpha^{(0,k)}_{[(i,m),(\mathrm{j,n})]} \cdot \sum_{(q,t)\in N_S} D_{(q,t)} \cdot \alpha^{(q,t)}_{[(i,m),(\mathrm{j,n})]} \cdot \frac{1}{c_{[(i,m),(\mathrm{j,n})]}} \middle| \forall [(i,m),(\mathrm{j,n})] \in A\right\}$ denotes the average loading waiting delay of source *(0,k)*.

3.3.4 Objective Function

As for an evacuation optimization scenario, we expect to evacuate the overall evacuees out of the emergency region as fast as we can. In other words, minimizing the network clearance time is always assigned with the first priority. Therefore, we set our first objective as minimizing the network clearance time.

Objective function 1: $\quad Minimize\colon\ \mu^*$

From another perspective, the throughput of the evacuation network is also expected to be maximized during the evacuation process. Since the severity of the emergency hazard or risk is relatively low at the beginning of the evacuation, it is always rational and reasonable to evacuate the people intensively during this early time period. This is sort of the concept of greedy algorithm that if we are not quite confirmed when there will be a "deadly hazards explosion", what we are preferring to do is to evacuate as many people as we can from the time point the evacuation alarm is distributed. As is illustrated in Figure 3-6, if there are two independent evacuation plans named Plan 1 and Plan 2, which have the same network clearance time, absolutely Plan 2 is much better than Plan 1 since its total in-network time is much lower. In other words, Plan 2 guarantees we can evacuate many more people earlier.

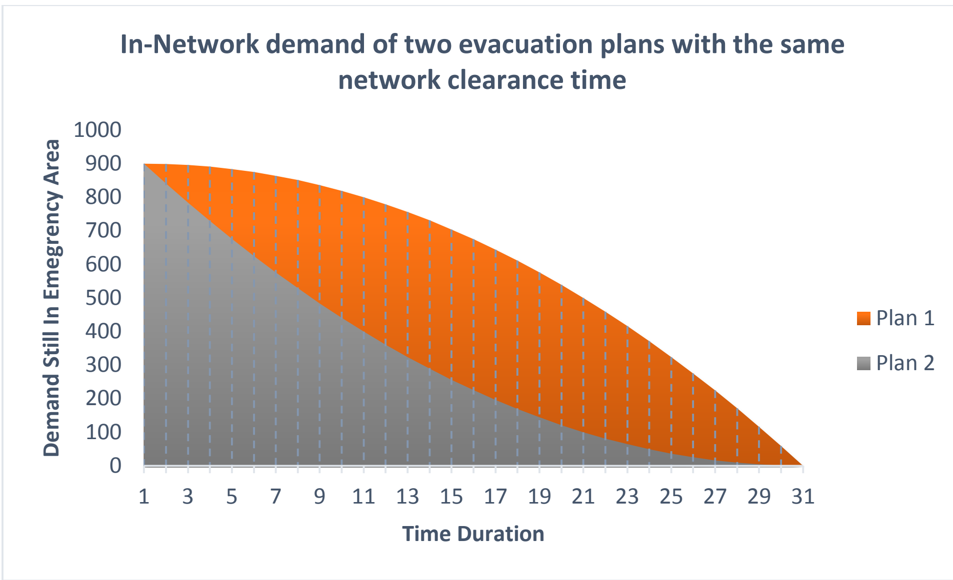


Figure 3-6: An example that two evacuation plan having same network clearance time but different total in-network time

Therefore, we set our second objective function as minimizing the total in-network time.

Objective function 2: $\quad\quad Minimize\text{: } \mathrm{T}_{\mathrm{in-net}}$

It is noted that the total in-network time also includes the total travel time during the evacuation process as we discussed in the previous section. In addition to the total evacuation travel time, the total in-network time also contains the total expected loading waiting delay, which is determined by the O-D routes' bottlenecks.

3.3.5 Constraints

Constraints of this model can be classified into three classes. The first class of constraints is related to the evacuation route connectivity and destination capacity limitation, and the second class of constraints deals with the intersection conflicts elimination. Finally, the third class of constraints further guarantees the routing consistency within intersection.

Before going through the description of constraints, the solution structure is necessary to be illustrated first. As is declared at the beginning of this chapter, the routing optimization model here aims to come up with a set of efficient evacuation routes to cope with the evacuee demand in one or multiple sources. First of all, we must guarantee that for each evacuee demand source, there must be at least one egress route assigned to it so that the evacuees can be successfully evacuated out. Exactly one egress route might be effective to a specific evacuation source if the total demand of this source is not that high (e.g. several hundreds of vehicles). However, when the evacuation demand in a particular source with multiple egresses is relatively high, only one evacuation route is likely to impede the evacuation efficiency. Hence, we need to make our routing optimization model capable of coming up with multiple evacuation routes for a particular source if it is necessary. To achieve this goal, we can take advantage of a simple network representation technique. The traditional method to represent a source within a network is just abstract it as a single network node with a provided demand. Here we can choose to duplicate a specific source as multiple dummy nodes. They have the same geographical information but only the demand on each duplicated dummy node changes. As is shown in Figure 3-7, if we divide a single source node into four geographically identical dummy source nodes and use our routing optimization model to calculate based on this revised network, we can come up with at most four different evacuation routes for the original source. Further, if the optimized routes for all of the duplicated dummy nodes are the same, we conclude that the best routing plan for this original source is to use only one egress route. Putting it this way, we are able to use the most basic network connectively constraints to guarantee that there is at least one outgoing rout for each of the evacuation source.

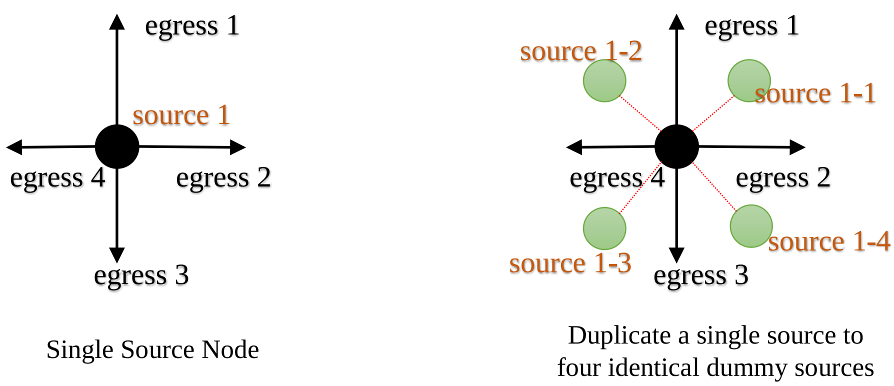


Figure 3-7: Method of transform a single source node into several parallel dummy nodes

First Class Constraints (Route Connectivity and Destination Capacity):

$$\sum_{(j,n)\in\mu^{-}[(0,k)]} \alpha_{[(0,k)(j,n)]}^{(0,k)} = 1$$

$$\text{for each source node } (0,k) \qquad (1)$$

$$\sum_{(\mathrm{j,n})\in\mu^{+}[(\mathrm{i,m})]} \alpha^{(0,\mathrm{k})}_{[(\mathrm{j,n}),(\mathrm{i,m})]} - \sum_{(\mathrm{j,n})\in\mu^{-}[(\mathrm{i,m})]} \alpha^{(0,\mathrm{k})}_{[(\mathrm{i,m}),(\mathrm{j,n})]} = 0$$

$$\text{for each source node } (0,\mathrm{k}), \text{ and each transshipment node } (\mathrm{i,m}) \text{ of } (0,\mathrm{k}) \qquad (2)$$

$$\sum_{(\mathrm{i,m})\in\mu^{+}[(\mathrm{j,n})]} \alpha^{(0,\mathrm{k})}_{[(\mathrm{i,m})(\mathrm{j,n})]} = 1$$

$$\text{for each } (0,\mathrm{k}) \in \mathrm{N_s}, \text{and } (\mathrm{j,n}) \text{ equal to } \mathrm{N_0} \qquad (3)$$

$$\sum_{\forall(0,k)} \sum_{(\mathrm{i,m})\in\mu^{+}[(\mathrm{j,n})]} D_{(0,k)} \alpha^{(0,\mathrm{k})}_{[(\mathrm{i,m})(\mathrm{j,n})]} \le C_{(j,n)}$$

$$\text{for each } (\mathrm{j,n}) \in \mathrm{N_d} \qquad (4)$$

It is noted that the source node *(0,k)* mentioned in the above formulations can either be an original source node or a duplicated dummy source node. This is up to the abstracted network structure. Notations $\mu^{-}[(i,m)]$ and $\mu^{+}[(i,m)]$, respectively, represent set of successor nodes and set of predecessor nodes of node *(i,m)*. Constraint (1) guarantees that for each source node, there is exactly one route outgoing from it. Constraint (2) indicates that, for each transshipment node, if a route goes into it, then the route must go out. Constraint (3) guarantees that for each source node there must be a sink node allocated to it. Constraints together (1-3) say that for each source node there is exactly one egress route linking it to a sink node. Constraint (4) limits the allocated evacuee demand at a specific exit point by considering the capacity of this destination node (e.g. shelter capacity or exiting freeway capacity).

Second Class Constraints (Movement Conflicts Elimination)

As is discussed at the beginning of this chapter, most of the evacuation delays and inefficiencies are coming from stop-and-go controls, especially in an urban area. However, many of the evacuation optimization studies ignored the significant role of intersection or freeway interchanges, and they just deemed the intersection as a network node in their modeling. The optimization results of the models that treat the issue this way might be far more inaccurate in comparison with that in a real world scenario. For instance, turn movements at an intersection are always operating at a much lower speed. Thus, too many turn movements at an intersection make the intersection a bottleneck. This fact can never be recognized if the intersection is just simplified as a network node. As a consequence, more and more researchers in the evacuation literature are beginning to consider how to construct uninterrupted evacuation flows in terms of intersection control, which is proved to greatly shorten the evacuation process, e.g. Cova and Johnson (2003), Xie et al. (2010), Bretschneider and Kimms (2011), Liu and Luo (2012).

Bretschneider and Alf Kimms (2011) first presented a mathematical formulation of the intersection conflicts elimination in terms of the intersection-related constraint described in Cova and Justin (2003). The model here takes advantage of the work in Bretschneider and Alf Kimms (2011) and presents a more general form of the conflicts elimination constraints.

$$\gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} \leq 1, \forall h \in L_{[(i,m),(i,n)]}, \forall k \in R_{[(i,m),(i,n)]}$$

$$\gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} \leq 1, \forall h \in R_{[(i,m),(i,n)]}, \forall k \in L_{[(i,m),(i,n)]}$$

$$\text{for each intersection node } (i,m), \text{and } \forall n \notin \{(m \bmod \theta_i) + 1, (\theta_i + m - 2) \mathrm{mod} \theta_i + 1\} \tag{5}$$

Constraints (5) guarantee that there are no movement conflicts depicted in Figure 3-8, i.e. conflict between two arcs with no common nodes. The above inequality equations are suitable for any general intersections. In other words, they are applicable to intersections with four or more legs. (In real world situations, a four-leg intersection is more common).

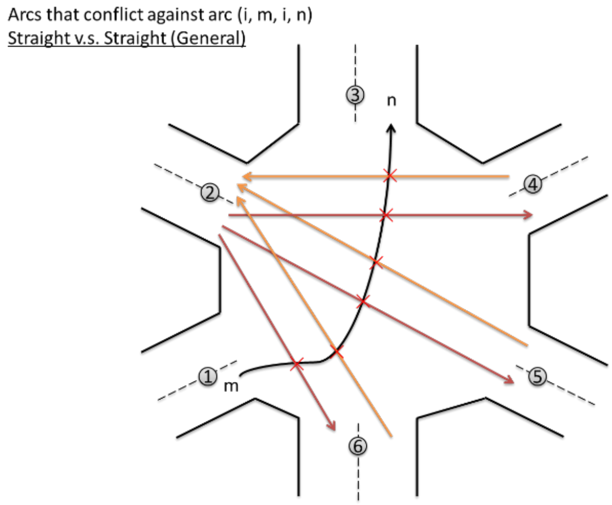


Figure 3-8: Arcs that conflict with arc [(i,m),(i,n)] with no common nodes

$$\gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} \leq 1, \forall\ k \in L_{[(i,n),(i,m)]} \text{ and } h = n$$

$$\text{for each intersection node } (i, m), \text{and } \forall n \neq (\theta_i + m - 2) \bmod \theta_i + 1 \qquad (6)$$

$$\gamma_{[(i,m),(i,n)]} + \gamma_{[(i,h),(i,k)]} \leq 1, \forall\ h \in L_{[(i,n),(i,m)]} \text{ and } k = m$$

$$\text{for each intersection node } (i, m), \text{and } \forall n \neq (\theta_i + m - 2) \bmod \theta_i + 1 \qquad (7)$$

Constraints (6) and (7) eliminate the movement conflicts of the type depicted in Figure 3-9, i.e. conflict between two arcs with exactly one common node (i.e. straight versus left turn or left turn versus left turn). The above inequalities are suitable for any general intersection. In other words, they are applicable to intersections with three or more legs. (In real world situations, three-leg and four-leg intersections are more common. Five or more leg intersections are not common but can be seen in some urban areas, e.g. Downtown of Washington D.C.)

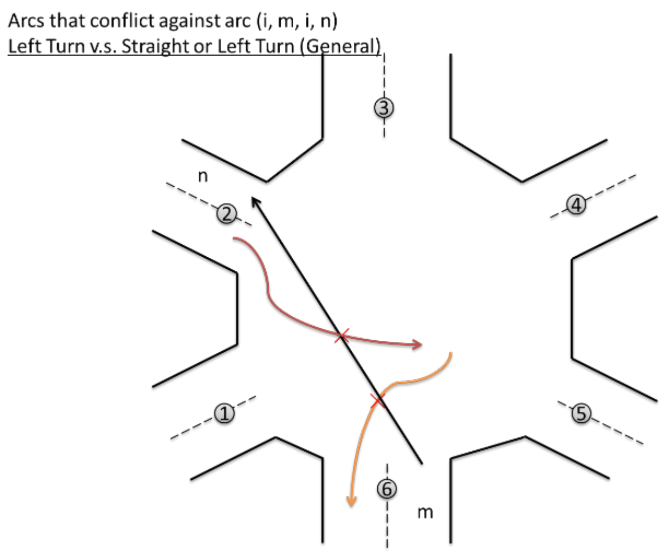


Figure 3-9: Arcs that conflict with arc [(i,m),(i,n)] with exactly one common node

In addition, to maintain the routing consistency within a controlled intersection, constraints (9) with the introduction of a big number M are added to the model (i.e. if an intersection arc is prohibited then it cannot be used by any route).

$$\sum_{(0,k)\in N_S} \alpha_{[(i,m),(i,n)]}^{(0,k)} \leq M \cdot \gamma_{[(i,m),(i,n)]},$$

$$\text{for each intersection arc } [(i,m),(i,n)] \text{ within intersection i} \qquad (9)$$

$$\alpha_{[(i,m),(\mathrm{j},\mathrm{n})]}^{(0,k)} \text{ and } \gamma_{[(i,m),(i,n)]} \in \{0,1\} \qquad (10)$$

3.4 Solution Approach

Due to the bi-level characteristics and nonlinearity of the objective functions demonstrated above, the optimization problem cannot be directly solved with the current algorithms implemented in LP solvers, e.g. CPLEX, Gurobi, etc. Hence, a specific solution approach for the optimization model is developed and introduced in this section. To begin with, the bi-level objective functions are recalled here:

Objective function 1, MINIMIZE:

$$\mu^* = \max\{\sum_{\forall(0,k)} \frac{D(0,k)\cdot \alpha^{(0,k)}_{[(i,m),(\mathrm{j},\mathrm{n})]}}{c_{[(i,m),(\mathrm{j},\mathrm{n})]}} | \forall \text{ arc } [(\mathrm{i},\mathrm{m}),(\mathrm{j},\mathrm{n})] \in \mathrm{A}\}$$

Objective function 2, MINIMIZE:

$$\mathrm{T}_{\mathrm{in-net}} = \sum_{(0,k)\in N_S} D_{(0,k)} \cdot E[\mathrm{TW}_{(0,\mathrm{k})}] + \sum_{(0,k)\in N_S} D_{(0,k)} \cdot \sum_{[(i,m),(\mathrm{j},\mathrm{n})]\in A} [\alpha^{(0,k)}_{[(i,m),(\mathrm{j},\mathrm{n})]} \cdot t_{[(i,m),(\mathrm{j},\mathrm{n})]}]$$

Where, $E[TW_{(0,k)}] = \frac{1}{2}\cdot \max\left\{\alpha^{(0,k)}_{[(i,m),(\mathrm{j},\mathrm{n})]} \cdot \sum_{(q,t)\in N_S} D_{(q,t)} \cdot \alpha^{(q,t)}_{[(i,m),(\mathrm{j},\mathrm{n})]} \cdot \frac{1}{c_{[(i,m),(\mathrm{j},\mathrm{n})]}} \middle| \forall[(i,m),(\mathrm{j},\mathrm{n})] \in A\right\}$

Observing the structure of the first objective function (i.e. minimizing the network clearance time), we can understand that μ^* represents the total serving time of the network bottleneck, which is exactly the link having the largest total serving time in the evacuation process. In other words, we are minimizing the upper bound of the total serving times among the overall network links. Thus, we can introduce an upper bound T in terms of the total serving time for each link and aggregate these newly inequalities into our constraints pool.

$$\frac{1}{c_{[(i,m),(\mathrm{j},\mathrm{n})]}} \cdot \sum_{(0,k)\in N_S} D_{(0,k)} \cdot \alpha^{(0,k)}_{[(i,m),(i,n)]} \leq \mathrm{T}, \forall[(i,m),(i,n)] \in A \tag{11}$$

At this time point (i.e. eliminating the first objective function by adding a set of new constraints), we obtain a sub-problem with regard to a particular T. For each sub-problem, this pre-fixed upper bound T is exactly the term we want to minimize in our original problem (i.e. the network clearance time). In each sub-problem, inequality constraints (11) guarantee that the total serving time of each evacuation link is bounded by duration T. Actually this can be viewed as another way to mitigate the routing congestion.

Now let us observe the structure of the second objective function (i.e. minimizing the total in-network time). This objective function consists of two independent parts, the first one is the total loading waiting time that is determined by the egress routes' arrival demand, and the second one is the total evacuation travel time that only is determined by the routes' length. After introducing the new sets of upper bound constraints to the original problem, we can see that a pre-fixed upper bound T not only limits the total serving time of the network bottleneck (i.e. network clearance time), but also put a limit to the total serving time of each individual link. It is just the total serving time of each individual link that determines the expected total loading waiting delay expressed as the first part of objective function 2. Putting it another way, a lower pre-fixed upper bound T in constraints (11) not only lowers the network clearance time, but also automatically reduces the expected total loading waiting delay as a part of objective function 2. Therefore, if we introduced a pre-fixed upper bound T as the constraints for each individual link, we can simply use the total travel time as our sub-problem's performance indicator. Hence, a linear sub-optimization problem with regard to a pre-fixed T can be written as below,

---

Objective function:

$$Minimize: \sum_{(0,k)\in N_S} D_{(0,k)} \cdot \sum_{[(i,m),(\mathrm{j,n})]\in A} [\alpha^{(0,k)}_{[(i,m),(\mathrm{j,n})]} \cdot t_{[(i,m),(\mathrm{j,n})]}]$$

Subject to:

Constraints: (1) - (10), and,

$$\frac{1}{c_{[(i,m),(\mathrm{j,n})]}} \cdot \sum\nolimits_{(0,k)\in N_S} D_{(0,k)} \cdot \alpha^{(0,k)}_{[(i,m),(i,n)]} \le \mathrm{T}, \forall [(i,m),(i,n)] \in A \quad (11)$$

Intuitively speaking, when the evacuation demand is very large, a relatively small T of each link is more attractive to the system optimization. This indicates that the evacuation demand is distributed more evenly among the network links such that the total loading waiting delay will correspondingly decrease. Instead, the sub-optimization problem with a large T only seeks for the shortest evacuation route of each evacuation source, regardless of the loading waiting delay. Thus, we can start to solve the sub-optimization problem with a relatively small T and iteratively increase it until each of the sources chooses the shortest path to the destination. By solving and comparing each of these sub-optimization problems, we are guaranteed to find a close-to optimal solution to the original bi-level nonlinear programming model. The calculation process is further described in Figure 3-10.

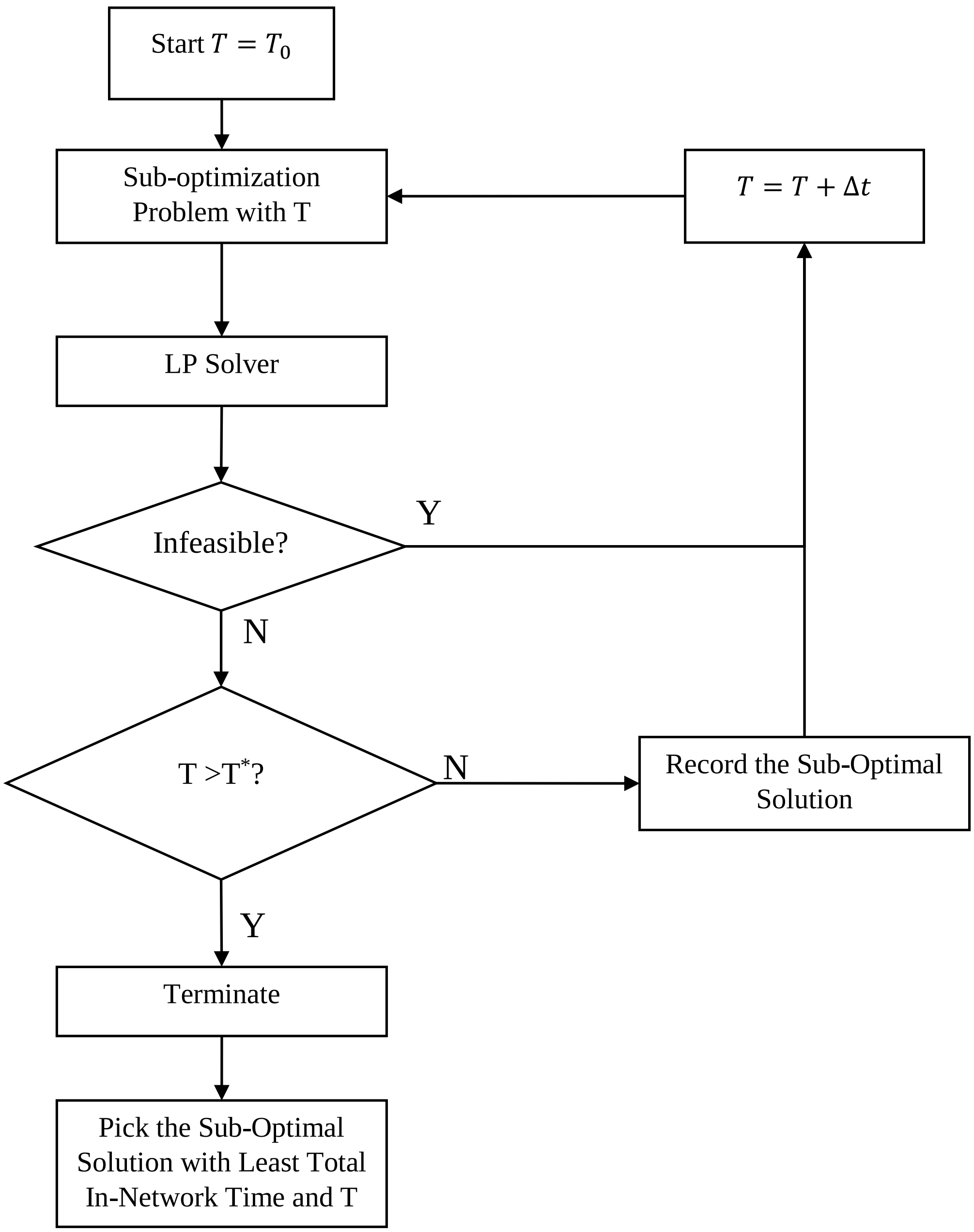


Figure 3-10: Flow Chart of the Routing Optimization Solution Approach

Chapter 4 : Scheduling Optimization Model

4.1 Introduction

The optimization model in Chapter 3 generates a set of evacuation route(s) for each source from a macroscopic perspective. Since the evacuation demand is high, the overall demand cannot realistically be loaded into the network simultaneously. Thus, a scheduling strategy based on which the demand is efficiently discharged is necessary. This chapter aims to develop an optimal scheduling model to further determine the departure rate of each source. There are two types of methodology that optimally determine the scheduling information: a linear programming approach based on a time-space network, and a heuristic approach. In considering the high evacuation demand (e.g. millions of vehicles), which will need an extremely large time-space network, the heuristic approach proves to be more efficient in dealing with such an optimization problem (Lu et al. (2005)).

Lu et al. (2005) propose an optimal algorithm to solve routing and scheduling optimizations with the objective of minimizing the total evacuation time in a capacitated network. The experimental tests on this algorithm present pretty good results. Although they claim this algorithm is suitable in an evacuation scenario, they do not provide any specific evacuation scenarios that can directly adopt it. However, in terms of the evacuation situation studied in this paper (i.e. vehicle based evacuation), the algorithm will be invalid due to two reasons: (1) conflicted traffic flows cannot move on simultaneously at an intersection, and (2) the network node (i.e. intersection or freeway interchange) is not able to store any demand (evacuee vehicles). In other words, in the highway-based evacuation scenario, once a group of vehicles is loaded into the network, they have to move until reaching their destination. This is quite different from the scenario of a building evacuation, in which a demand group can be temporarily stored in a transshipment node (e.g. a big space in the building). Therefore, based on their greedy scheduling concepts, we developed a simulation based scheduling heuristic to dynamically determine the discharge rate for each source. The output of routing optimization model in Chapter 3 are set as the input of this heuristic. Moreover, in order to be more realistic, the interplays among traffic flow are incorporated in this heuristic by attaching a mesoscopic traffic simulator. The corresponding traffic simulator and algorithm are described separately in the following sections.

4.2 Traffic Simulator

For the scheduling heuristic, a mesoscopic traffic simulator implemented by Afshar and Haghani (2008) is taken advantage of in this chapter. The Pseudo code of the traffic simulator is described in Table 4-1.

4.3 Scheduling Heuristic

Before introducing the scheduling heuristic, some necessary assumptions are made as shown below.

Assumptions:

1) Roadway capacity is constant, which is equal to the traffic flow at the critical density;
2) Evacuation priority of each source is predefined, and the evacuation priority ranking approaches can be referred to in Church and Cova (2000);

Table 4-1: Pseudo Code of the Traffic Simulator

Load network

Load demand (Loading vehicles from each Source)

For each time interval *t*,

    For each link *a*,

        Identify number of vehicles entering the link from each O-D path

        Identify number of vehicles leaving the link to their O-D path

        Identify number of vehicles present in the link

        Calculate link travel time by Equation (4.1)

        Assign exit time to vehicles entering link in current *t*

    Next Link

Next *t*, unless all vehicles have reached their destinations

---

$$v_i = \left(v_f - v_{min}\right) \cdot \left[1 - \alpha \left(\frac{k_i}{k_{jam}}\right)^{\beta}\right] + v_{min} \tag{4.1}$$

Where,

v_i = speed on link i

v_f = free flow speed on link i

v_{min} = minimum speed on link i

k_i = density on link i

k_{jam} = jam density on link i

α, β are sensitivity parameters

It is noted that this traffic simulator assumes vehicle speed on a particular link, which only depends on the prior and prevailing conditions of that link; traffic entering at a later time does not affect the travel speed of the vehicles already in the link.

In the above assumptions, the first one indicates that the roadway capacity is only determined by its geometry characteristics, i.e. number of lanes and free flow speed. It is always a fixed value during the flow dynamics. However, the roadway throughput is affected by the amount of traffic flow on it. As for the second assumption, the evacuation priority of each separate source is usually predefined according to their vulnerability. For example, in a hurricane or flood evacuation, the sources within the coastal area are always considered with a high evacuation priority since these areas are more vulnerable to the disasters.

As for the demand discharging process, we expect to make full use of the network capacity, since this can make the network provide the largest throughput. However, if the discharging rate is too high, the network will suffer a big congestion, which will in turn result a larger network clearance time. Therefore, the core is to find an appropriate time-dependent discharging rate for each source. In Chapter 3 we show that the maximal throughput of a specific route is determined by its bottleneck. The bottleneck of a specific route is identified by considering both its future arrival demand and its capacity. Here we define the bottleneck of a specific route r as,

$$l(\mathrm{r}) = \max\{\frac{\sum D(l)}{c(l)} | l \in r\}$$

where, $\sum D(l)$ is the total un-arrived demand of arc l and *c(l)* denotes the capacity of this arc. With this type of concept, the dynamic network loading heuristic is provided in Table 4-2.

Table 4-2: Pseudo Code of the Proposed Simulation based Scheduling Heuristic

Algorithm: Simulation-Based Capacity Constrained Scheduling Algorithm

Phase I (Initialization):

Input and Preprocessing:

1) Directed Network $\mathbf{G}(\mathbf{N}, \mathbf{A})$ with a set of nodes N and a set of arcs A;
2) Set of evacuation routes $\boldsymbol{R} = \{\boldsymbol{R}(\boldsymbol{n}) | \boldsymbol{n} \in \boldsymbol{N_s}\}$, where $\mathbf{R}(\mathbf{n}) = \{\mathbf{a}_{\mathbf{n}_1}, \mathbf{a}_{\mathbf{n}_2}, \cdots, \mathbf{a}_{\mathbf{n}_\mathbf{k}}\}$ and $\mathbf{a}_{\mathbf{n}_\mathbf{k}} \in \boldsymbol{A}$;
3) Demand $\mathbf{D}(\mathbf{n})$ of each route;
4) Evacuation priority $\mathbf{P}(\mathbf{n})$ of each source (route);
5) Capacity $\boldsymbol{c}(\mathbf{a}_{\boldsymbol{k}})$ of each arc $\mathbf{a}_\mathbf{k} \in \mathbf{A}$;
6) For each arc $\mathbf{a}_\mathbf{k}$, initialize its serving sets $\mathbf{S}(\mathbf{a}_\mathbf{k}) = \{\mathbf{n} | \forall \mathbf{n}\ \mathbf{and}\ \mathbf{a}_\mathbf{k} \in \mathbf{R}(\mathbf{n})\}$;
7) Loading attraction factor for each source $\boldsymbol{\alpha}$ (usually greater than 1), and discharging reduction factor $\boldsymbol{\beta}$ (usually smaller than 1, but should be strictly smaller than $\boldsymbol{\alpha}$)
8) Heuristic Time interval $\Delta\mathbf{t}$, during which a batch of vehicles will be discharged
9) Set the initial time point of the simulation with t = 0;

Notations in the calculation iteration:

(1) $\boldsymbol{L}(\boldsymbol{n}, \boldsymbol{t})$: Time-dependent maximal discharging rate of source n at time interval t

(2) $\boldsymbol{\theta}_{\boldsymbol{a}_{\boldsymbol{k}}}(\boldsymbol{t})$: Time-dependent flow attraction factor of arc $\mathbf{a}_\mathbf{k}$

(3) $\boldsymbol{Discharge}(\boldsymbol{n}, \boldsymbol{t})$: Number of vehicles discharged from source n during time interval $(\boldsymbol{t}, \boldsymbol{t} + \Delta\mathbf{t})$

(4) $\boldsymbol{\Gamma}$: Total number of vehicles getting out of the network by time point t

(5) $\boldsymbol{Arrived}(\boldsymbol{t} - \Delta\mathbf{t}, \boldsymbol{t})$: Number of vehicles exiting the network within time interval

$(\boldsymbol{t} - \Delta\mathbf{t}, \boldsymbol{t})$

Phase II (Loading Iteration):

Do

Determine the flow attraction factors for each arc $\mathbf{a_k}$ by using the following logics:

For each arc $\mathbf{a_k} \in \boldsymbol{A}$:

If $\mathbf{a_k}$ is congested (i.e. traffic density is over than its critical density):

Set $\boldsymbol{\theta_{a_k}(t) = \beta}$

Else

Set $\boldsymbol{\theta_{a_k}(t) = \alpha}$

End

For each source n with route R(n) and demand $\mathbf{D(n) > 0}$:

Determine its maximal potential discharging rate according to the capacity as well as the flow attraction factor of each arc $\mathbf{a_k} \in \mathbf{R(n)}$ by using the following logic function:

$$\boldsymbol{L(n,t)} = \mathbf{min}\{\boldsymbol{\theta_{a_k}(t)} \cdot \mathbf{c(a_k)} \frac{\boldsymbol{P(n)}}{\sum_{\boldsymbol{n' \in S(a_k)}} \boldsymbol{P(n')} \cdot \mathbf{1}_{\{\boldsymbol{D(n')>0}\}}} \,|\forall\, \mathbf{a_k} \in \boldsymbol{R(n)}\}$$

Determine the amount of vehicles to be discharged from source n by using the following logic:

$$\boldsymbol{Discharge(n,t)} = \mathbf{min}\{\boldsymbol{D(n)}, \boldsymbol{L(n,t)} \cdot \Delta\mathbf{t}\}$$

Update the remaining demand of source n:

$$\boldsymbol{D(n) = D(n) - Discharge(n,t)}$$

End

Load the determined discharged vehicles into the simulation network;

Run Traffic Simulator for duration $\Delta\mathbf{t}$;

Update the simulation clock by: $\mathbf{t} = \mathbf{t} + \Delta\mathbf{t}$

Update and record the number of exiting vehicles by:

$$\boldsymbol{\Gamma} = \boldsymbol{\Gamma} + \boldsymbol{Arrived}(\boldsymbol{t} - \Delta\mathbf{t})$$

While: $\boldsymbol{\Gamma} < \sum \boldsymbol{D}(\boldsymbol{n})$

A brief flow chart of this algorithm is demonstrated in Figure 4-1: Flow Chart of the Simulation based Scheduling Heuristic.

In the above algorithm, two heuristic factors are introduced. They are, loading attraction factor α and discharging reduction factor $\boldsymbol{\beta}$. This is because even though the traffic congestion of a specific route is due to the total arrived demand from multiple sources, these separate demands might not be arriving at this bottleneck simultaneously, especially at the beginning of the evacuation process. If we determine the discharge rate for these sources strictly according to the capacity of their prescriptive routes, there might be capacity waste within some time period due to the different arrival time of the flow from these sources. Thus, during the evacuation process, we expect to fully make use of the roadway capacity by introducing this loading attraction factor α. However, this might also cause traffic congestion if these flows nearly arrive at the same network link simultaneously. Therefore, we additionally introduce the reduction factor $\boldsymbol{\beta}$. It aims to reduce the traffic congestion, which is caused by the loading attraction factor α. In other words, if a link (not necessary the current bottleneck) suffers a traffic congestion, the reduction factor will decrease the discharging rate of its sources below the normal condition in the next iteration. In addition, the evacuation priority of each source is also taken advantaged of to determine its discharging rate. The incorporation of the source specific priority in the loading heuristic is simple. That is, the roadways' capacities are divided and reserved for each of the sources based on their weighted evacuation priorities. As is indicated in the above algorithm, a source with a relatively high evacuation priority is usually assigned with a larger discharging rate by reserving more roadway capacity for it. This is further illustrated in the numerical experiment of the real world scenario at the end of Chapter 5.

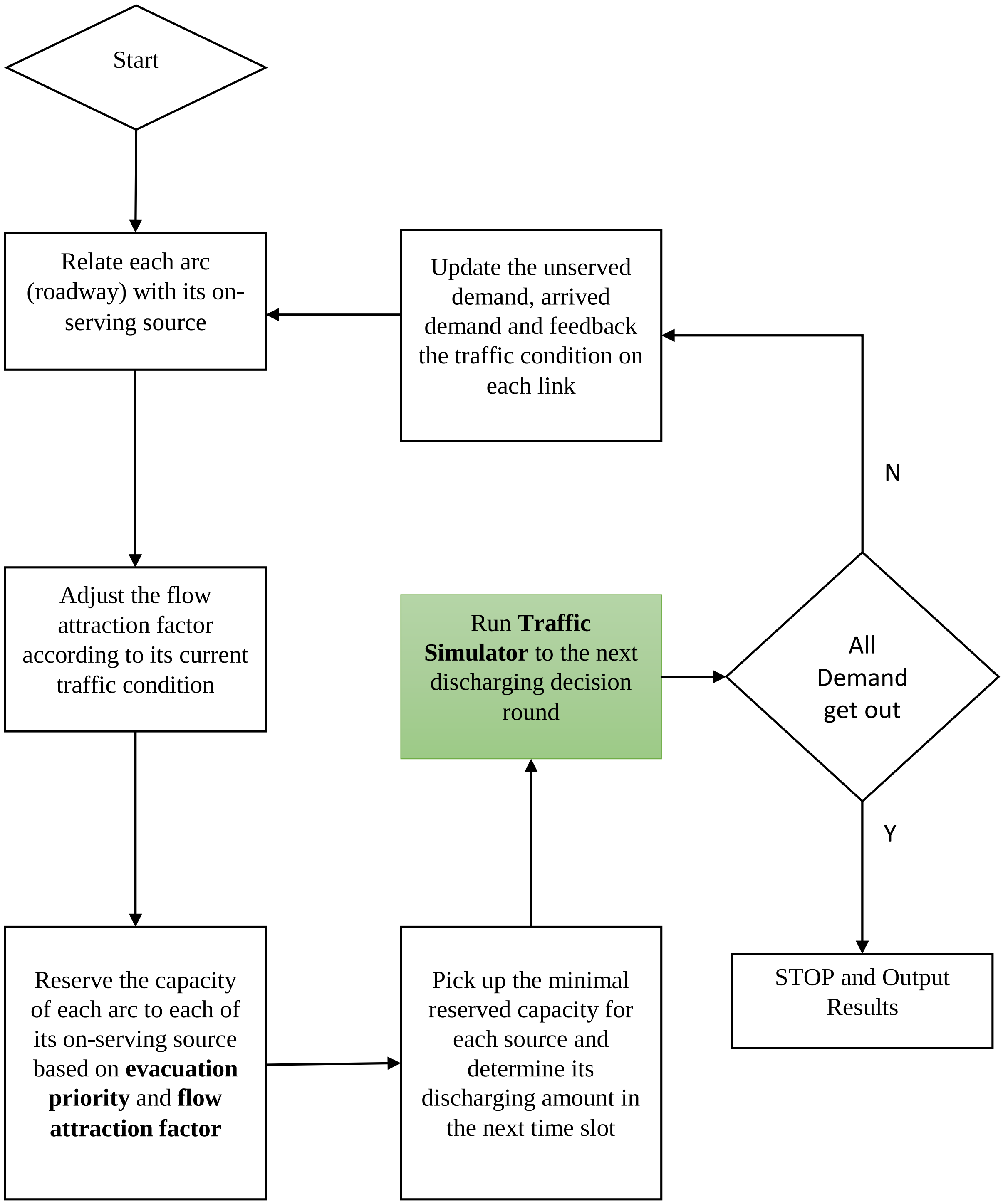


Figure 4-1: Flow Chart of the Simulation-based Scheduling Heuristic

Chapter 5 : Case Study

5.1 Introduction

In this chapter, numerical experiments are conducted in terms of two scenarios. The first case study is a based on a fabricated urban grid network with totally 16 intersections, 9 evacuation sources and 6 safety destinations. The second case study is conducted upon a real-world scenario of Maryland Eastern Shore evacuation with pre-selected optional evacuation networks and real-world demand. The experiment parameters and corresponding results analysis are demonstrated and discussed in the following sections.

The computation experiment of the numerical study is in Windows 8.1 operating system environment running on an X64-processor-based computer with CPU 2.60GHz and 6.00 GB memory. The routing optimization model in Chapter 3 is implemented with C++ and CPLEX_12.51 Concert in Visual Studio 2012. The scheduling simulation model in Chapter 4 is implemented with C++ STL in Visual Studio 2012.

5.2 Case Study I

5.2.1 Problem Definition

A case study is conducted to test and demonstrate the aforementioned optimization model with a fictional evacuation network described in Figure 5-1. There are a total of nine evacuation sources and six safety destinations, i.e. sources: (0, 1), (0, 2), (0, 3), (0, 4), (0, 5), (0, 6), (0, 7), (0, 8) and (0, 9), and sinks: (20, 1), (20, 2), (20, 3), (20, 4), (20, 5), (20, 6). In addition, a dummy sink node (0, 0) is constructed by linking a virtual arc from each safety destination. The travel time and capacity on each virtual arc are assumed to be 0 and infinity, respectively. The rectangle areas in Figure 5-1 represent intersections, and arcs within the rectangles indicate the movement directions at the corresponding intersection. There are a total of 222 arcs and 69 nodes, including the dummy node in the example network. Without loss of generality, we assume the capacity of each real roadway equals to 1,200 vehicles per hour. The corresponding travel time on each intersection arc is three seconds; on each general roadway, it is one minute. In addition, the evacuation demand on each source is equal to 300 vehicles. It is noted that the routing optimization model does not consider lane reversal optimization. However, as is explicitly shown, the six exit links can be fully taken advantage of during the evacuation process. Therefore, in the following calculation, we double the capacity of each exit link. In other words, we assume no traffic flow gets into the network through the evacuation via the exit links.

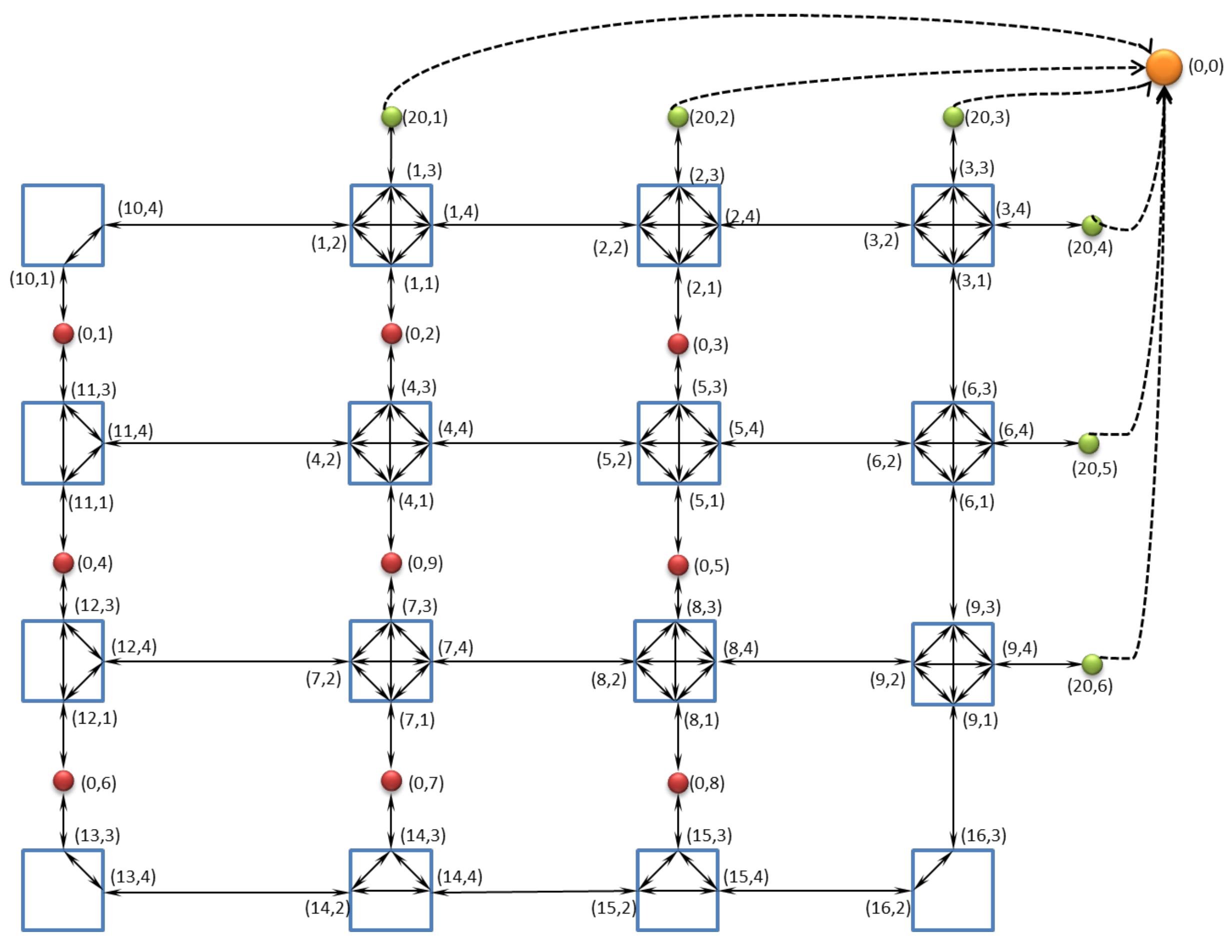


Figure 5-1: Evacuation Network of Case Study 1

5.2.2 *Demonstration of the Routing Optimization Procedure*

At the beginning of the optimization process, we first transform the original routing optimization model into numerous sub-optimization problems. To solve the problem with high resolution, we use the time unit minutes instead of hours. The iterative results of the corresponding optimization process are described in Table 5-1 and Figure 5-2. In addition, details of each routing plan are described in Table 5-2, Table 5-3, Table 5-4 and Table 5-5.

Table 5-1: Optimized Routing Plan for each T (network clearance time)

T (minutes or iterations)	Solution Status	Routing Plan	Total Waiting Delay	Total Travel Time	Total Evacuation Time
0 ~ 30	Infeasible	N/A	N/A	N/A	N/A
30 ~ 44	Feasible	Routing Plan 1	34875	9915	44790
45 ~ 59	Feasible	Routing Plan 2	49500	9600	59100
60 ~ 67	Feasible	Routing Plan 3	63000	9600	72600
68 ~ 134	Feasible	Routing Plan 4	42750	9600	52350
135 +	Feasible	Routing Plan 3	63000	9600	72600

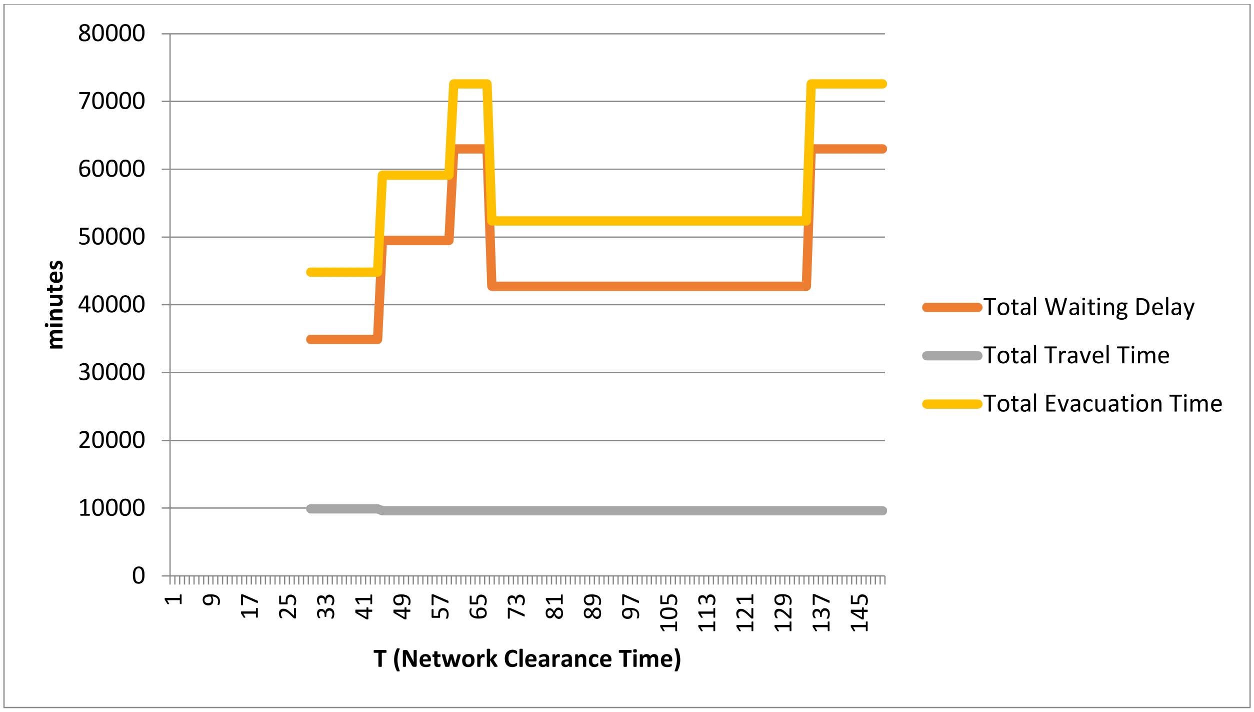


Figure 5-2: Optimal Value versus Different T

With the above iteration results, a sub-optimal solution is found, i.e. routing plan 1. Although routing plan 1 has a relatively larger total travel time than the other three plans, the total waiting delay of this plan is significantly smaller. Therefore, routing plan 1 is chosen as the ultimate optimal solution from the perspective of total evacuation time. However, routing plan 1 cannot be explicitly proved to be the optimal solution of the original nonlinear binary programming problem, but it is satisfactory enough since it reduces the total evacuation time by nearly 40 percent in comparison with the shortest path evacuation strategy (i.e. Routing Plan 3).

Table 5-2: Routing Plan 1 for Case Study 1

Source Node	Route	Bottleneck
(0,1)	(0, 1)->(10, 1)->(10, 4)->(1, 2)->(1, 3)->(20, 1)->(0, 0)	(10,4)->(1,2)
(0,2)	(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(1,3)->(20,1)
(0,3)	(0, 3)->(2, 1)->(2, 3)->(20, 2)->(0, 0)	(0,3)->(2,1)
(0,4)	(0, 4)->(11, 1)->(11, 3)->(0, 1)->(10, 1)->(10, 4)->(1, 2)->(1, 3)->(20, 1)->(0, 0)	(10,4)->(1,2)
(0,5)	(0, 5)->(5, 1)->(5, 4)->(6, 2)->(6, 4)->(20, 5)->(0, 0)	(5,4)->(6,2)
(0,6)	(0, 6)->(12, 1)->(12, 4)->(7, 2)->(7, 4)->(8, 2)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,7)	(0, 7)->(14, 3)->(14, 4)->(15, 2)->(15, 4)->(16, 2)->(16, 3)->(9, 1)->(9, 4)->(20, 6)->(0, 0)	(9,4)->(20,6)
(0,8)	(0, 8)->(8, 1)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,9)	(0, 9)->(4, 1)->(4, 3)->(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(1,3)->(20,1)

Table 5-3: Routing Plan 2 for Case Study 1

Source Node	Route	Bottleneck
(0,1)	(0, 1)->(10, 1)->(10, 4)->(1, 2)->(1, 3)->(20, 1)->(0, 0)	(1,3)->(20,1)
(0,2)	(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(0,2)->(1,1)
(0,3)	(0, 3)->(2, 1)->(2, 3)->(20, 2)->(0, 0)	(0,3)->(2,1)
(0,4)	(0, 4)->(11, 1)->(11, 4)->(4, 2)->(4, 3)->(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(0,2)->(1,1)
(0,5)	(0, 5)->(5, 1)->(5, 4)->(6, 2)->(6, 4)->(20, 5)->(0, 0)	(5,4)->(6,2)
(0,6)	(0, 6)->(12, 1)->(12, 4)->(7, 2)->(7, 4)->(8, 2)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,7)	(0, 7)->(7, 1)->(7, 4)->(8, 2)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,8)	(0, 8)->(8, 1)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,9)	(0, 9)->(4, 1)->(4, 3)->(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(0,2)->(1,1)

Table 5-4: Routing Plan 3 for Case Study 1

Source Node	Route	Bottleneck
(0,1)	(0, 1)->(10, 1)->(10, 4)->(1, 2)->(1, 3)->(20, 1)->(0, 0)	(1,3)->(20,1)
(0,2)	(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(0,2)->(1,1)
(0,3)	(0, 3)->(2, 1)->(2, 3)->(20, 2)->(0, 0)	(0,3)->(2,1)
(0,4)	(0, 4)->(11, 1)->(11, 4)->(4, 2)->(4, 3)->(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(0,2)->(1,1)
(0,5)	(0, 5)->(8, 3)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,6)	(0, 6)->(12, 1)->(12, 4)->(7, 2)->(7, 4)->(8, 2)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,7)	(0, 7)->(7, 1)->(7, 4)->(8, 2)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,6)
(0,8)	(0, 8)->(8, 1)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,9)	(0, 9)->(4, 1)->(4, 3)->(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(0,2)->(1,1)

Table 5-5: Routing Plan 4 for Case Study 1

Source Node	Route	Bottleneck
(0,1)	(0, 1)->(10, 1)->(10, 4)->(1, 2)->(1, 3)->(20, 1)->(0, 0)	(10,4)->(1,2)
(0,2)	(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(1,3)->(20,1)
(0,3)	(0, 3)->(2, 1)->(2, 3)->(20, 2)->(0, 0)	(0,3)->(2,1)
(0,4)	(0, 4)->(11, 1)->(11, 3)->(0, 1)->(10, 1)->(10, 4)->(1, 2)->(1, 3)->(20, 1)->(0, 0)	(10,4)->(1,2)
(0,5)	(0, 5)->(5, 1)->(5, 4)->(6, 2)->(6, 4)->(20, 5)->(0, 0)	(5,4)->(6,2)
(0,6)	(0, 6)->(12, 1)->(12, 4)->(7, 2)->(7, 4)->(8, 2)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,7)	(0, 7)->(7, 1)->(7, 4)->(8, 2)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,8)	(0, 8)->(8, 1)->(8, 4)->(9, 2)->(9, 4)->(20, 6)->(0, 0)	(8,4)->(9,2)
(0,9)	(0, 9)->(4, 1)->(4, 3)->(0, 2)->(1, 1)->(1, 3)->(20, 1)->(0, 0)	(1,3)->(20,1)

The scheduling heuristic demonstrated in Chapter 4 is used to simulate the overall evacuation process of each sub-optimal routing plan. Figure 5-3 depicts the relationship between in-network demand and evacuation time. The simulation results indicate that the network clearance time for routing plan 1, plan 2, plan 3 and plan 4 are 38 minutes, 55 minutes, 72 minutes and 59 minutes, respectively.

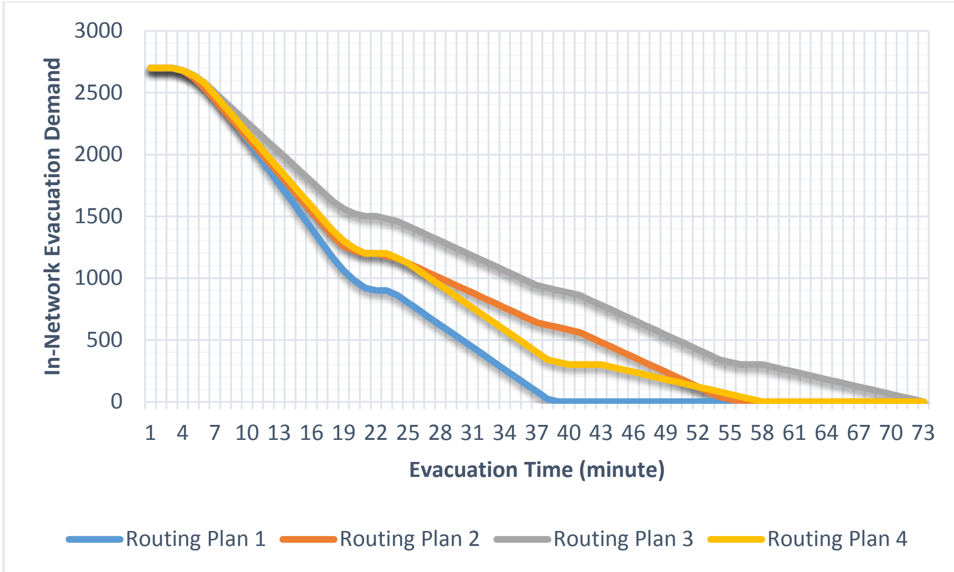


Figure 5-3: In-Network Evacuation Demand V.S. Evacuation Time

5.3 Case Study II

5.3.1 Problem Introduction and Statement

The Eastern Shore of Maryland is located east of Chesapeake Bay and consists of nine of the state's counties. They are Caroline County, Cecil County, Dorchester County, Kent County, Queen Anne's County, Somerset County, Talbot County, Wicomico County, and Worcester County. This area has a population of around 420,000 (2004 census). However, the population of Ocean City in the summer peak season can reach 150,000 to 300,000 compared with 7,000 to 25,000 during the off-peak season. The large population as well as the unique geographic location make both the Ocean City and other recreation areas located in the shore vulnerable to the threat of hurricanes. In addition, as is shown in the map of Figure 5-4, there are only five outbound traffic egresses (i.e. Chesapeake Bay Bridge, MD-213, DE-71, DE-1 and DE-72) for this area, which emphasizes the need for designing a set of efficient emergency evacuation plans. The problem we are concerned with here is to find an efficient and effective evacuation plans including routing and scheduling in the case of natural disaster such as hurricane or flooding. To be more specific, given the evacuation demand from each location, we are aiming at finding an optimal evacuation routing strategy with the shortest duration (i.e. network clearance) and the maximal evacuation throughput (i.e. minimal total in-network time of the evacuees). Based on the routing plan and predefined evacuation priority (vulnerability), the departure scheduling arrangement will be further determined with the goal of mitigating the traffic congestion and maximizing the network throughput.

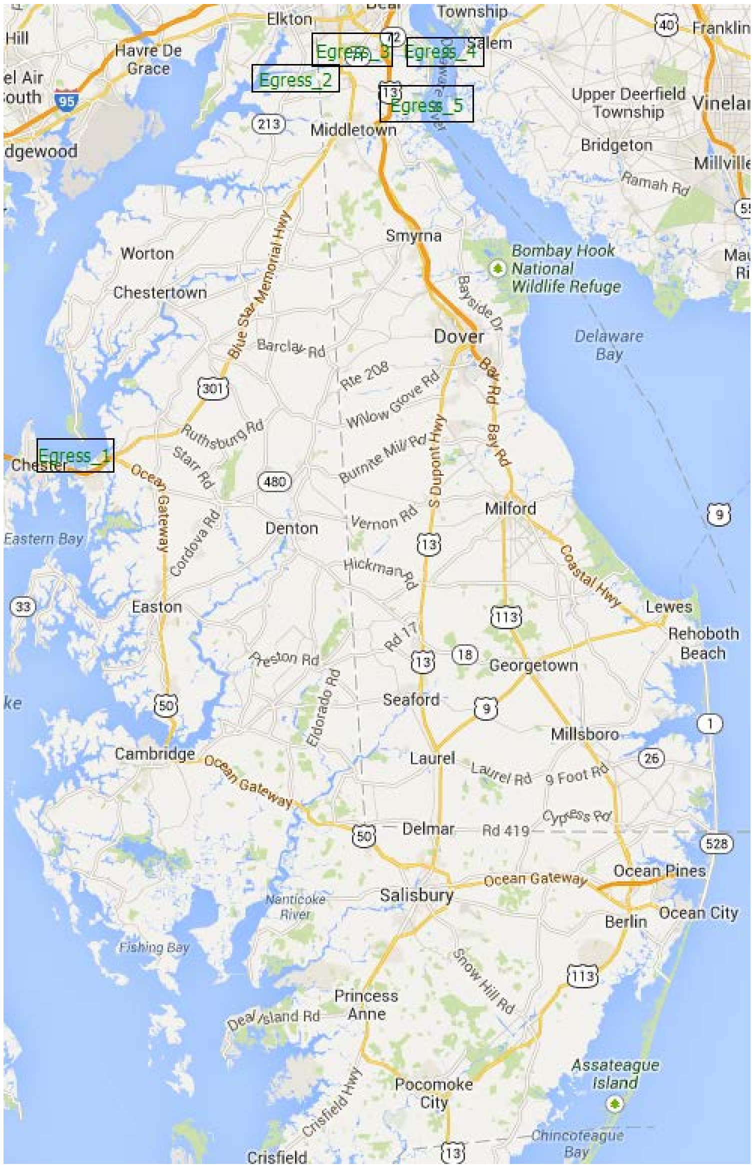


Figure 5-4: Map of Eastern Shore of Maryland

5.3.2 *Evacuation Network and Demand Description*

The evacuation network and demand data for the Eastern Shore of Maryland is provided by Afshar and Haghani (2007) in their final evacuation report to the Maryland SHA. The selection of the entire evacuation network was based on two complementary data sources, one is roads' map from Google and the other one is a detailed micro-simulation file in CORSIM. The geographic structure of the entire evacuation network is shown in Figure 5-5. With further refinement, the roadways that are not in the general evacuation direction are eliminated and the resulting network consists of all major outbound roadways (including both arterials and freeways) in the area of the Maryland Eastern Shore.

The amount and location of the major demand generation points (evacuation sources) are obtained by aggregating the sparsely distributed demand generation points. For example, if there are minor roads linking several different demand generation points to the same freeway entrance ramp or arterial entrance point and these demand generation points are geographically close to each other, then these demand points can be further aggregated to be a major demand point with access to the network. For instance, network point 16 shown in Figure 5-5 is a major demand point (with vehicle amounts approximately to 114,000) located in Salisbury City with several major freeway ramps. Here the sparsely distributed evacuation demand point within the area of Salisbury City are aggregated and deemed as a major source point, since these separate demand points have the same entrance points (or access) to the major evacuation network. In other words, the role of the minor roadways is to connect all of these closed demand generation points and lead them to the ramps or arterial accesses of the major evacuation network.

Figure 5-5: Major Evacuation Network for Maryland Eastern Shore[2]

It is noted that the aforementioned evacuation network (Figure 5-5) is a hybrid network, consisting of both arterials and freeways. Each link represents either an arterial segment or a freeway corridor. It does not contain any specific information about the freeway ramps and arterial intersections. Each network node is just indicating the connectivity of different roadway segments. If we directly use it to conduct some calculation or optimization, the result we obtain will be far more inaccurate as is already discussed in Chapter 3. As the simple example demonstrated in Figure 5-6, there are two intersecting freeways 1-3 and 2-4 and their capacities are 4,000 veh/hr for each one. If we simply assume the interchange between them is a node, and use this topology structure to optimizing the flow routes and calculate the evacuation time, the result might be far more different from the real-world scenario. That is mainly because the ramp connecting them has a much lower capacity than any of these two major freeways. This is actually true in most of the cases in the real world. Similarly, as for the case of arterials with intersection as their connection point, if we just viewed the intersection as a single network node, the movement conflicts and turning capacity will be totally ignored. This is the reason why more and more evacuation researchers begin to consider modeling the intersection as a sub-network in their routing optimization.

To estimate the evacuation time and optimize the routing plan more precisely, we further construct the sub-network for each of the intersections and freeway interchanges based on the real-world roadway parameters and incorporate the sub-networks into the original network. Google map is taken advantage of as a major reference to estimate the sub-network parameters (e.g. freeway flow speed, number of lanes, length and the corresponding traffic flow capacity). In addition, type of the sub-network is also identified, i.e. either intersection sub-network or controlled-access sub-network.

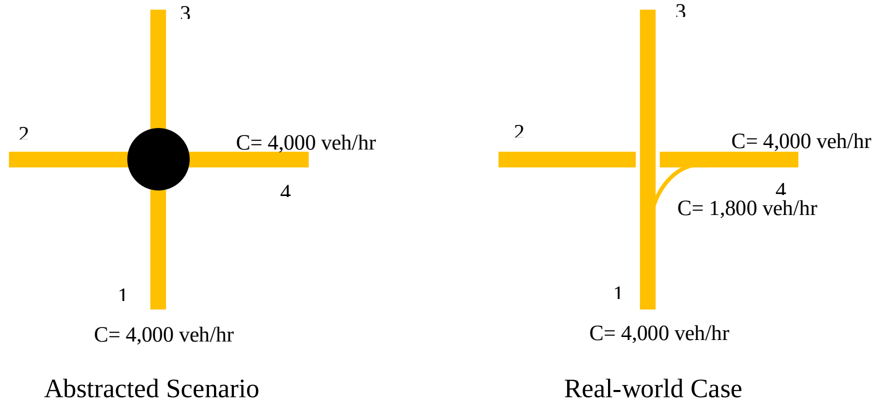
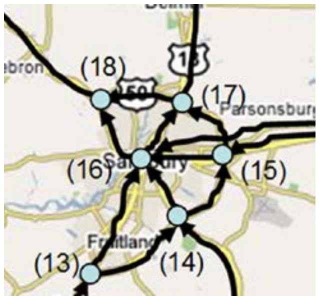


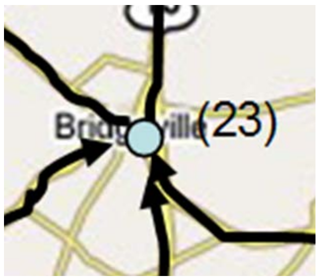
Figure 5-6: Case that the interchange capacity is overestimated

Before providing the detailed sub-network information at each intersection or freeway interchange, it is necessary to mention that there are four special network nodes, which neither belong to the type of intersection nor the interchange section between freeways. They are, node 16, 22, 23 and 29, which denote Salisbury, Federalsburg, Bridgeville and Denton, respectively (Figure 5-7). Actually, these four nodes are dummy nodes representing a central area of a small town (center of a major demand source). There are many minor roadways inside these dummy nodes connecting all of the demand generation points, therefore, we assume that the flow capacity within them are very high and just consider them as large transshipment nodes.

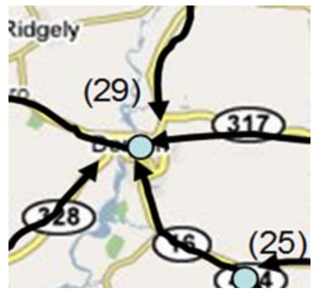


Dummy Node 16

Dummy Node 22



Dummy Node 23



Dummy Node 29

Figure 5-7: Four special network nodes (Dummy node) in case study II

Among all of the 50 network nodes demonstrated in Figure 5-5, totally 20 of them are arterial intersections with at most four legs. They are, node 11, 12, 2, 3, 6, 8, 10, 49, 19, 20, 21, 24, 25, 50, 28, 30, 33, 34, 36, 39 and 40. Without loss of generality, all of traffic movements within these intersections can be further represented by the following network structure (Figure 5-8). Actually, for intersection with three legs, this sub-network structure can also be used to model its insider movements, and we just need to disable the 4th node *(i,4)* and all of the links connected with it (i.e. only using the first three sub-nodes). As is illustrated in Chapter 3, constraints (5 - 7) can be used to eliminate all of the movement conflicts within this intersection sub-network (merge and diverge are as movement conflicts here).

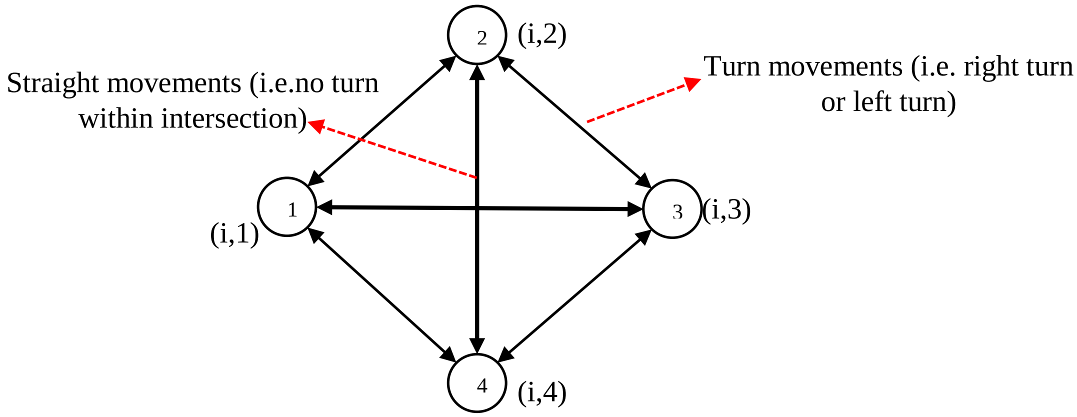


Figure 5-8: Sub-network representation for intersection with at most four legs

In addition to the various types of network nodes mentioned above in the studied evacuation network, there is another type of transshipment node that cannot be ignored, i.e. the controlled-access region (i.e. interchange) between freeways. Due to the geometric properties of freeways, there does not exist any traffic conflicts within the controlled-access region. Thus the traffic conflicts elimination constraints are not required for this type of sub-networks (e.g. traffic flow 1->3 is not conflicted with traffic flow 2->4). Only the capacities of the interchange ramps make a difference (Figure 5-9).

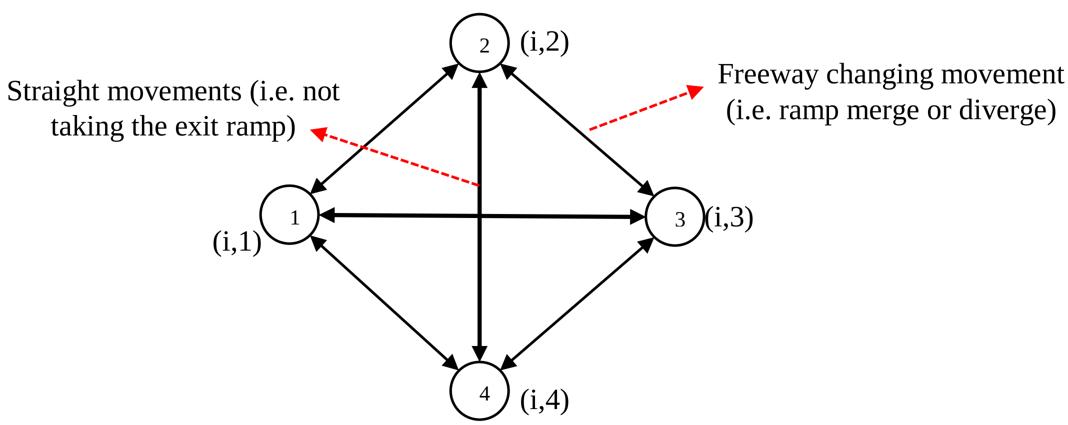


Figure 5-9: Sub-network representation for interchange between freeways

For each arterial intersection or freeway interchange, we use the aforementioned labeling method to label the sub-network nodes. For example, node *49* is an arterial intersection with 3 legs, we label the sub-network nodes inside this intersection as *(49,1), (49,2) and (49,3).* The directed link *(49,1)-(49,2)* means the movement from the 1^{st} leg to the 2^{nd} leg within this intersection. Moreover, for any dummy node, non-intersection and non-interchange node, we simple label it with *(n,0)*, where *n* is the ID of this node in the original network. For example, directed link *(1,0)-(4,4)* means the movement from source node *1* to the 4^{th} leg of intersection node *4.*

5.3.3 Numerical Experiments

In this section, routing optimization is conducted upon the given evacuation network demonstrated in the last section. Totally 192080 evacuation demand is considered within this network. The demand distribution is shown in the Table 5-6. Here we assume each source is a node, because we can reasonably view each node as an access point to the major evacuation network in the real-world scenario. In other words, in each sub-region of the evacuation area, the demand has to get into the evacuation network through these access points, e.g. controlled ramps of the freeway, and collectors to the major arterial.

To begin with, we consider exactly one route for each of the sources, and use the routing optimization model to figure out these evacuation routes. By taking advantage of the solution approach demonstrated at the end of chapter 3, we find the optimal solution with minimal network clearance time 30 hours, total evacuation time 653611 hours and total in-network time 3.34082e+006 hours. The corresponding evacuation routes of this optimal solution are listed as below.

Table 5-6: Evacuation Demand Distribution in Eastern Shore Maryland

Source Node	Total Demand (Vehicles)
2	45,850
1	43,830
3	20,700
9	20,000
20	17,400
26	16,800
16	11,400
40	6,400
36	6,200
46	3,500

Table 5-7: Optimized Evacuation Routes (one route per source)

Source	Optimized evacuation route	Bottleneck (network link)	Average Network-Loading Waiting Time (hour)
1	1->4->5->8->10->49->21->50->27->48->44	(1,0)-(4,4)	14.95
16	16->17->19->23->25->29->30->47->31->32	(23,0)-(25,4)	12.84
2	2->1->4->45->7->15->16->17->19->23->24->28->35->39->43	(1,0)-(4,4)	14.95
26	26->30->31->32	(31,1)-(31,2)	14.60
3	3->6->10->49->21->23->25->29->30->31->32	(31,1)-(31,2)	14.60
36	36->47->31->32	(31,2)-(32,0)	8.44
40	40->42	(40,3)-(42,0)	2.13
46	46->11->13->16->18->20->26->30->31->32	(31,1)-(31,2)	14.60
9	9->10->49->21->50->27->48->44	(10,2)-(49,1)	14.09
20	20->26->30->31->32	(31,1)-(31,2)	14.60

From the results of Table 5-7 we can see, 8 out of the 10 routes have the bottleneck located in the intersection or freeway interchange region. Actually, this is always ignored if we do not consider the movement within intersection and freeway interchange as a sub-network. In other words, if we just simply view the arterial intersection or freeway interchange as a single node (indicating the connectivity of two roadways), we are not able to identify the bottleneck, which indicates the network clearance time, properly. The estimated network clearance time for the above routing strategy is around 30 hours. However, an argument might occur regarding this amount of network clearance time, since there exists multiple egresses for each source while we only optimize the routing problem by assigning exactly one route to each of these sources. In other words, the question is that if we assign more than one route to some of the sources can we obtain a lower network clearance time.

Before we further seek for multiple routes optimization results, we introduce a lover bound calculation technique for the network clearance time. Suppose a directed network *G(N,A)*, where *N* denotes the set of network nodes and *A* denotes the set of network arcs. Let *S* be the set of all source nodes within *G* and *T* be the set of all exit arcs (link connected to sink nodes) of *G*. Then the network clearance time must have a lower bound calculated by,

$$\mathrm{L}_{\mathrm{NC}} = \sum_{n \in S} d(n) \Big/ \sum_{(i,j) \in T} c(i,j)$$

where, $d(n)$ denotes the demand at source n, and *c(i,j)* denotes the capacity of arc *(i,j)*. This lower bound of network clearance time is very obvious, since all of the arcs in set T (i.e. exit arcs) constitute the minimal cut between this evacuation network and the outside regions. In other words, even though every non-exit link inside the network has an infinite capacity and zero travel time, the throughput of this network can never exceed its total exit links' capacity.

Now we can take advantage of this technique to check the lower bound of the network clearance time for the Eastern Shore Maryland in two ways. The first one is that considering the entire Eastern Shore region as a whole, we can directly calculate this value. The second one is that we consider a sub-network of this whole region by referring the minimal cut of this sub-network (i.e. the ocean city island, since it possesses half of the total demand). The lower bounds of the network clearance time by taking these two ways are,

- Considering the entire region as a whole, the corresponding exit arcs are 31-32, 40-41, 40-42, 39-43 and 48-44. The capacities of these five exiting links are 4500, 1250, 1500, 3000 and 3000 in vehicles per hour, respectively. The total demand within this whole region is 192080 vehicles. Hence,

$$\mathrm{L}_{\mathrm{NC\_1}} = \frac{192080}{4500 + 1250 + 1500 + 3000 + 3000} = 14.49\ hours$$

- Considering the ocean city island as a sub-network, the corresponding exit arcs (i.e. the minimal cut from the rest of the network) are 1-4, 2-5, 3-6 and 9-10. The capacities of these four exiting links of ocean city are 3000, 1500, 1000 and 1000. The total demand in ocean city is 130380 vehicles. Hence,

$$\mathrm{L}_{\mathrm{NC\_2}} = \frac{130380}{3000 + 1500 + 1000 + 1000} = 20.05\ hours$$

Therefore, we derive a lower bound of the network clearance time for the whole network, which is $\mathrm{L}_{\mathrm{NC}} = \min\{L_{NC_1}, L_{NC_2}\} = 20.05\ hours$

In comparison with the lower bound (i.e. 20.05 hours), the optimal routing strategy with exactly one route for each source is not that desirable, since its network clearance time is around 30 hours. A careful examination of the network structure and the demand distribution indicates that each optimal route has to burden a huge amount of demand. However, the route capacity compared with its serving demand is very small, which is of high possibility to lead to a large clearance time. Therefore, it is necessary to investigate whether enlarging the number of evacuation route for each of the sources is effective to further minimize the network clearance. Hence, two more optimization experiments are additionally conducted. These are, assigning each source with two evacuation routes and assigning each source with three evacuation routes. This can be done by taking advantage of the “Dummy-Node” technique introduced in Chapter 3 (i.e.

replicating the single source node by multiple dummy nodes with the original demand evenly re-distributed). The optimization results indicate that enlarging the number of the evacuation routes for each source to 3 indeed decreases the network clearance time. The optimal network clearance times are 22.0 hours for the two-route strategy and 20.7 hours for the three-route strategy. The corresponding routing results are shown in Table 5-8 and Table 5-9, respectively.

It is noted that in the multiple-route routing strategies (at most 2-route per source and at most 3-route per source), the multiple optimized routes for a given source node might overlap with the other one(s). In some cases, the resulting egress routes for a given source might even be completely the same. For example, for the optimized evacuation routes with two routes per source instance, the two routes of source 26 are completely same. However, this type of solution is not contradictory with the definition “2-route evacuation plan”, because this solution indicates that if we assign two routes for source 26, the optimal routing plan for each route is 26->30->47->31->32. In other words, even in the 2-route optimization problem, the best routing plan for this source is using only one route. Therefore, this type of solution provides the optimization approach great flexibility. We can think it as “at most two routes assignment” problem. Moreover, the performance indicator for the three different routing plans (i.e. network clearance time, total travel time and total in-network time) defined in Chapter 3 are compared in Figure 5-10. As is shown, the “at most three routes” optimization approach gives a pretty good solution with the network clearance time 20.7 hours, which is only 3.24% larger than the lower bound (20.05 hours). Meanwhile, with the lower network clearance time, both of the “at most two routes” and “at most three routes” evacuation plans have a much smaller total in-network time than the “exactly one route” evacuation plan. In addition, the total travel time of these three routing plans are similar with each other. That is due to the objective function, which aims to seek a solution with a minimal total travel time. The total travel times of the last two routing plans are a little bit larger than that of the first routing plan. These results can be referred to the route structure of each plan. In the last two routing plans, some detours are generated to avoid larger bottleneck, i.e. minimizing the network clearance time.

Table 5-8: Optimized Evacuation Routes (two routes per source)

Source	Optimized evacuation route	Bottleneck (network link)	Average Network-Loading Waiting Time (hour)
1	1->4->45->7->15->17->19->23->24->28->35->39->43 1->2->3->6->10->49->21->50->27->48->44	(1,0)-(4,4) (3,2)-(6,1)	10.923 10.957
16	16->17->19->23->24->28->35->39->43 16->17->19->23->25->29->30->47->31->32	17,3-19,4 30,3-47,1	9.0025 10.95
2	2->5->8->10->49->21->50->27->48->44 2->1->4->45->7->15->16->18->20->26->30->31->32	10,2-49,1 30,1-30,2	10.8067 10.9563
26	26->30->47->31->32 26->30->47->31->32	30,3-47,1 30,3-47,1	10.95 10.95
3	3->2->1->4->45->7->15->16->17->19->23->25->29->30->47->31->32 3->2->1->4->45->7->15->17->19->23->24->28->35->39->43	30,3-47,1 1,0-4,4	10.95 10.9233
36	36->47->31->32 36->47->31->32	31,2-32,0 31,2-32,0	9.20833 9.20833
40	40->42 40->42	40,3-42,0 40,3-42,0	2.13333 2.13333
46	46->11->13->16->18->20->26->30->31->32 46->11->13->16->18->20->26->30->31->32	40,3-42,0 40,3-42,0	10.9563 10.9563
9	9->10->49->21->50->27->48->44 9->10->49->21->50->27->48->44	10,2-49,1 10,2-49,1	10.8067 10.8067
20	20->26->30->31->32 20->26->30->31->32	30,1-30,2 30,1-30,2	10.9563 10.9563

Table 5-9: Optimized Evacuation Routes (three routes per source)

Source	Optimized evacuation route	Bottleneck (network link)	Average Network-Loading Waiting Time (hour)
1	1->4->45->7->15->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
	1->4->45->16->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
	1->4->45->7->15->16->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
16	16->18->20->26->30->31->32	26,2-30,1	10.3415
	16->18->20->26->30->47->31->32	26,2-30,1	10.3415
	16->18->20->26->30->31->32	26,2-30,1	10.3415
2	2->1->4->45->7->15->16->18->20->26->30->31->32	26,2-30,1	10.3415
	2->5->7->15->17->19->23->24->28->35->39->43	17,3-19,4	10.2408
	2->5->8->10->49->21->50->27->48->44	2,2-5,4	10.1887
26	26->30->47->31->32	26,2-30,1	10.3415
	26->30->31->32	26,2-30,1	10.3415
	26->30->47->31->32	26,2-30,1	10.3415
3	3->6->10->49->21->50->27->48->44	3,2-6,1	10.35
	3->6->10->49->21->23->25->29->30->47->31->32	3,2-6,1	10.35
	3->6->10->49->21->50->27->48->44	3,2-6,1	10.35
36	36->47->31->32	31,2-32,0	8.60911
	36->47->31->32	31,2-32,0	8.60911
	36->47->31->32	31,2-32,0	8.60911
40	40->42	40,3-42,0	2.133
	40->42	40,3-42,0	2.133
	40->42	40,3-42,0	2.133
46	46->11->13->16->17->19->23->25->29->30->47->31->32	17,3-19,4	10.2408
	46->11->13->16->18->20->26->30->31->32	26,2-30,1	10.3415
	46->11->13->16->17->19->23->25->29->30->47->31->32	17,3-19,4	10.2408
9	9->10->49->21->50->27->48->44	31,2-32,0	9.999
	9->10->49->21->50->27->48->44	31,2-32,0	9.999
	9->10->49->21->50->27->48->44	31,2-32,0	9.999
20	20->26->30->31->32	26,2-30,1	10.3415
	20->26->30->31->32	26,2-30,1	10.3415
	20->26->30->47->31->32	26,2-30,1	10.3415

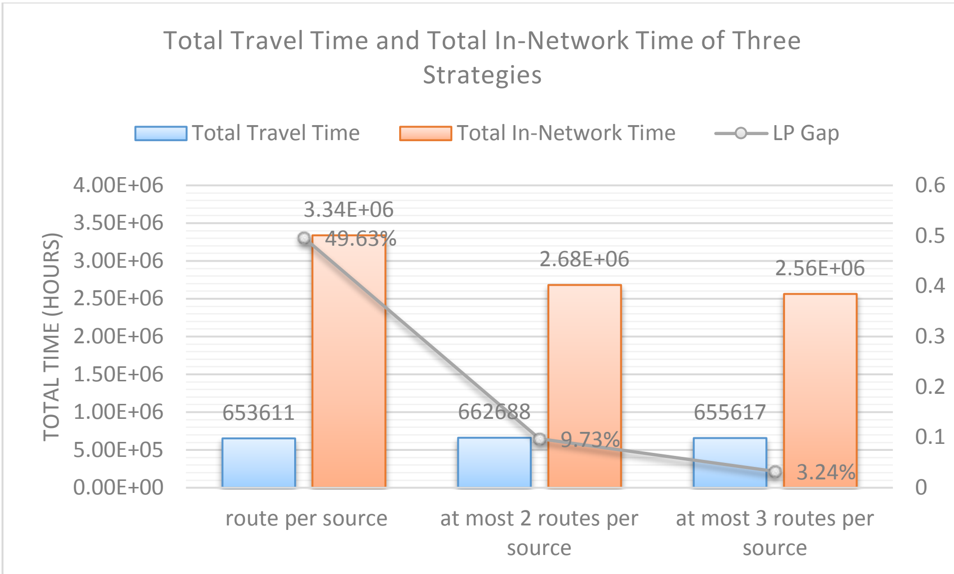


Figure 5-10: Comparison of performance indicators among the three proposed routing plans

Since the 3rd routing plan outperforms the other two, we accept it as the optimal routing strategy and run the scheduling heuristic based on it. Note that the simulation based discharging heuristic presented in Chapter 4 has two heuristic factors, the loading attraction factor α and discharging reduction factor β, which have a significant impact on the network clearance time. Recall that the loading attraction factor α aims to fully make use of the route capacity from a greedy perspective. While the discharging reduction factor β aims to relieve the traffic congestion resulted by α. Thus, choosing an appropriate pair of (α, β) is of great significance in determining the optimal discharging strategy. Actually, the value of the heuristic factors (α, β) is problem-specific. For example, if the evacuation route of each source is independent of the others (i.e. no link is going to be shared by more than two sources), the best discharging strategy is loading exactly according to the route bottleneck capacity. Therefore, for a specific evacuation scenario, it is necessary to conduct a set of sensitivity analysis to further figure out what the corresponding (α, β) pair should be. Based on the 3rd routing plan, sensitivity analysis of the heuristic factors (α, β) is conducted by running the simulation-based heuristic multiple times.

The time interval of the mesoscopic traffic simulator is chosen as 20 seconds in consideration of the average link length of the studied network. There is no doubt that the lower the simulation interval is, the higher simulation resolution will be. However it will substantially increase the simulation burden since we have millions of vehicles passing through the network. Results (i.e. network clearance time in seconds) with respect to different (α, β) pairs are shown and color-shaded in Table 5-10. The unit of the network clearance time is chosen as seconds in order to have a more clear view of the result values. As is shown in Table 5-10, the best simulation results are coming from the (α, β) pair equal to (1.6, 0.9). The corresponding network clearance time is 78,660 seconds (i.e. 21.85 hours). It is noted that, when the loading attraction factor α is fixed as 1.0, the network clearance time is always 99,200 seconds (i.e. 27.55 hours) and not sensitive to the change of the discharging reduction factor β. This is mainly because if we set the flow attraction factor as 1, all of the traffic flows will move under the critical traffic density. In other words, no traffic congestion will be detected by the heuristic. Thus, the discharging rate reduction will never be conducted during the loading process (i.e. discharging reduction factor β will never be used). However, if the loading attraction factor exceeds 1.0, which means there is a possibility that the traffic congestion occurs, an appropriate factor discharging reduction factor β will positively contribute to the evacuation by relieving the traffic congestion. For example, in this evacuation scenario, when the attraction factor α exceeds 2.0 (e.g. 2.2), a lower β (0.7) has a better discharging effect over the β equal to 0.9 or 0.8. In addition, the discharging reduction factor β should not be set as a very low value (e.g. below 0.5), otherwise the network clearance time will be very high, since a very low β over-reduces the discharging rate. In all, the loading attraction factor and discharging reduction factor should be chosen appropriately in order to make the evacuation process more stable. Either too large α or too low β will substantially increase the network clearance time by bringing too much variance to the system.

Since (α, β) equal to (1.6, 0.9) makes the discharging heuristic provide a set of traffic loading strategies with a more satisfactory network clearance time (i.e. 21.85 hours), we choose it as the heuristic factors in the scheduling algorithm described in Chapter 4 to come up with the discharging strategies. The corresponding time-dependent discharging rate is shown in Figure 5-11and Figure 5-12. The resulting evolution curve of the total evacuated demand is shown in Figure 5-13. The discharging rate is adjusted every 1 minute within the scheduling heuristic. As can be seen, the last group of vehicles is discharged at the time point around 1152 minute (i.e. 19.2). After that, it will take approximately 21.8 – 19.2 = 2.6 hours for all of the in-network vehicles to arrive at destinations.

In addition, we also investigate the impact of the evacuation priority on the evacuation process. As mentioned at the end of Chapter 4, the heuristic discharging rate of a particular source will be affected by its prescriptive evacuation priority. Further, the time-dependent discharging rate of a specific source will be high if it has a higher priority in comparison with other sources. Because we expect to allocate more network capacity to the source with a high priority. In this case study, sources located in Ocean City are assigned with a higher evacuation priority to see what happens if the scheduling Heuristic is operating in such a hybrid priority scenario. The corresponding results are shown in Figure 5-13 and Figure 5-14. From Figure 5-13 we can see, the network clearance time does not change too much for the scenario in which Ocean City has a larger priority. However, the time-dependent remaining demand in Ocean City area of the ‘Hybrid’ scheduling strategy is lower than that of the ‘Homogeneous’ strategy. In other words, if we assign a higher evacuation priority to the Ocean City area, the time-dependent throughput of its demand will increase. But the increased throughput will not be significant for this case (i.e. increasing the priority of the whole Ocean City Area). The intrinsic reason for this is that Ocean City has a huge percentage of the total evacuation demand in the whole Eastern Shore Area (i.e. 67.9%). In other words, the main competition of reserving the network capacity during the evacuation is coming from itself. Therefore, if we increase the evacuation priority of the Ocean City area simultaneously, the throughput of this area will be increased, but will not be that significant.

Table 5-10: Sensitivity Analysis of Network Clearance Time (sec) with Respect to Different (α, β) Pairs

		Discharging Reduction Factor (β)							
		0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2
Loading Attraction Factor (α)	1.0	99,200	99,200	99,200	99,200	99,200	99,200	99,200	99,200
	1.2	82,940	83,060	83,560	85,420	86,420	88,160	89,940	88,780
	1.4	79,600	80,460	81,620	83,420	84,460	86,440	89,500	93,400
	1.6	78,660	80,620	81,480	85,360	87,760	88,680	90,340	91,640
	1.8	79,220	80,500	81,780	85,400	88,160	88,980	91,320	96,220
	2.0	80,280	84,320	82,020	84,920	86,340	88,760	90,900	90,820
	2.2	83,840	86,600	82,200	85,180	88,000	89,720	91,340	91,880
	2.4	83,890	85,600	83,360	84,960	86,720	88,760	90,800	94,720
	2.6	84,000	85,740	82,680	85,200	88,880	89,740	90,400	92,340

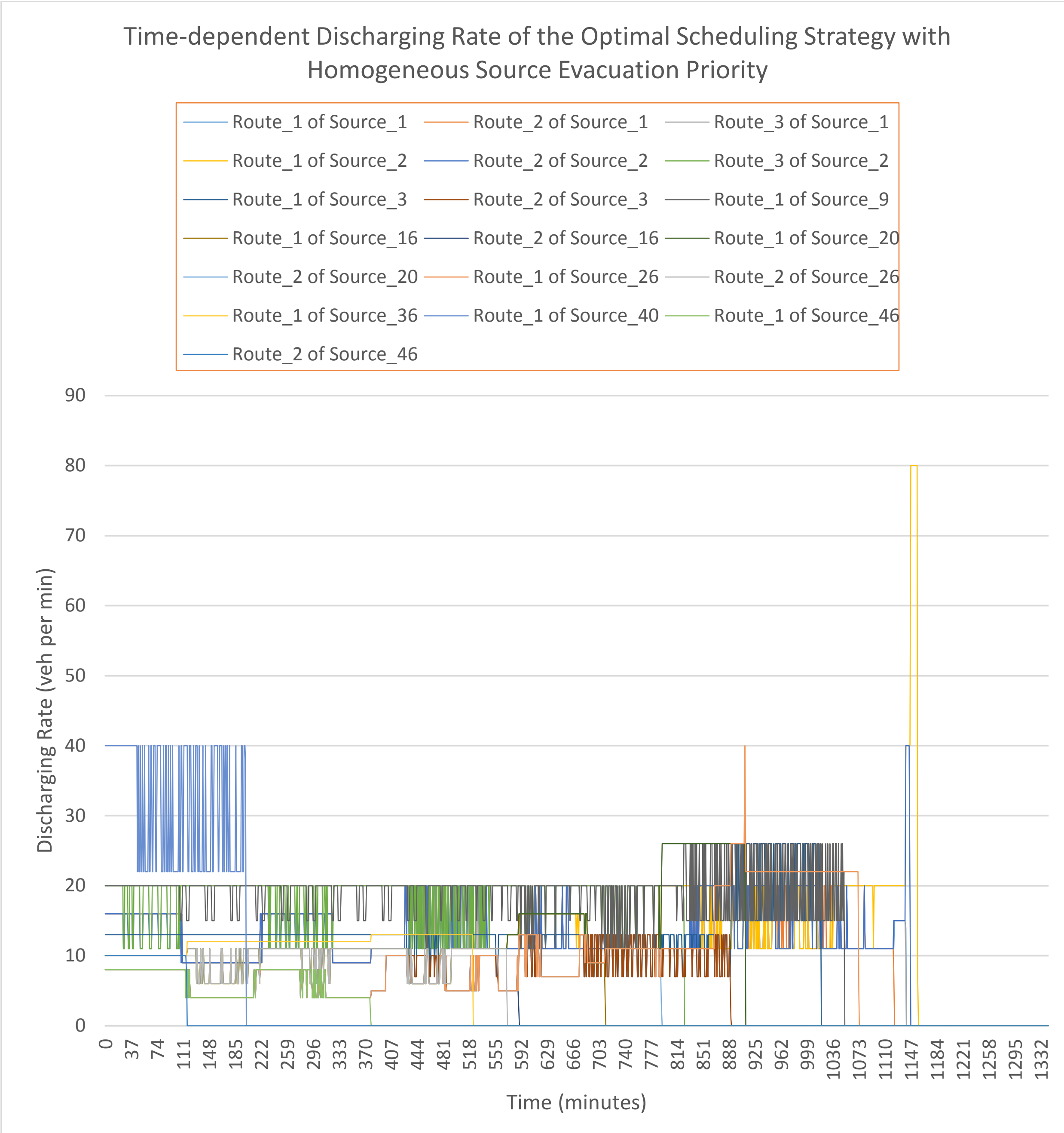


Figure 5-11: Time-dependent Discharging Rate of the Optimal Scheduling Strategy (All sources have the same priority 1)

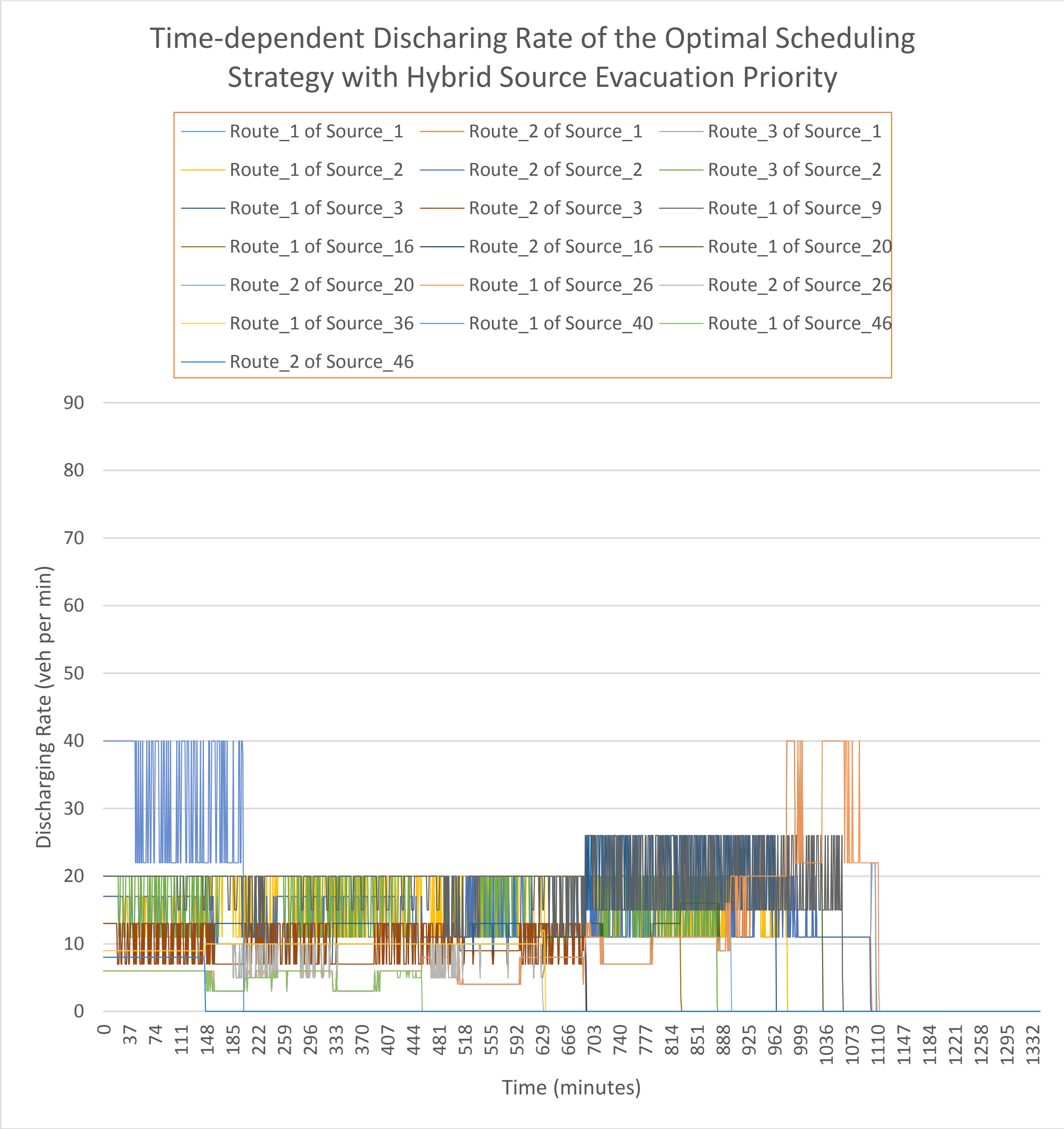


Figure 5-12: Time-dependent Discharging Rate of the Optimal Scheduling Strategy (Sources in Ocean city have a higher priority equal to 2, and other sources have priority 1)

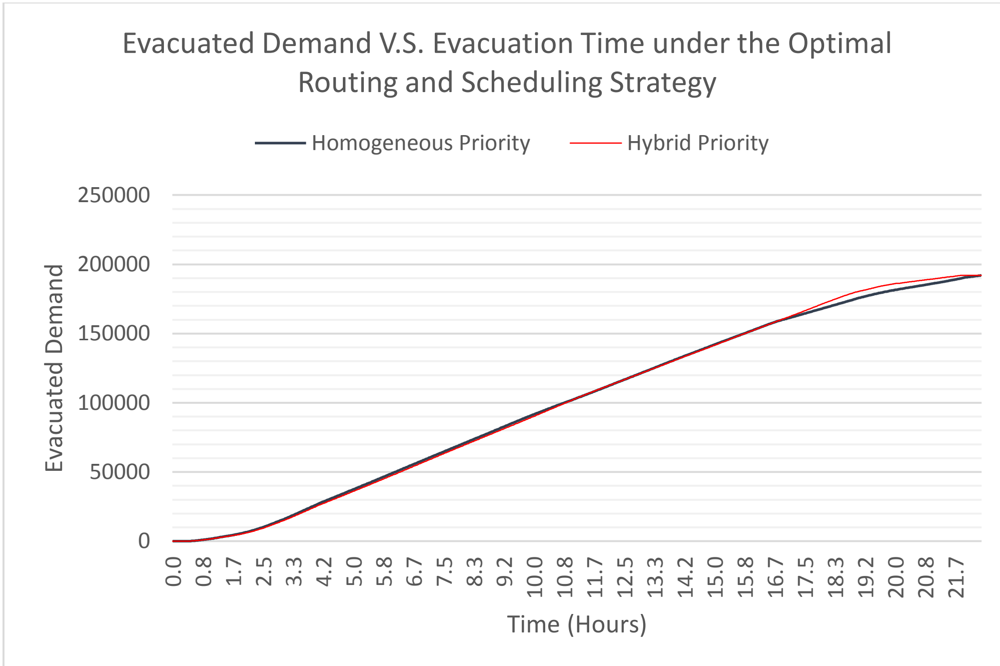


Figure 5-13: Time-Dependent Evolution Curve of the Total Evacuated Demand under the Optimal Routing and Scheduling Strategy

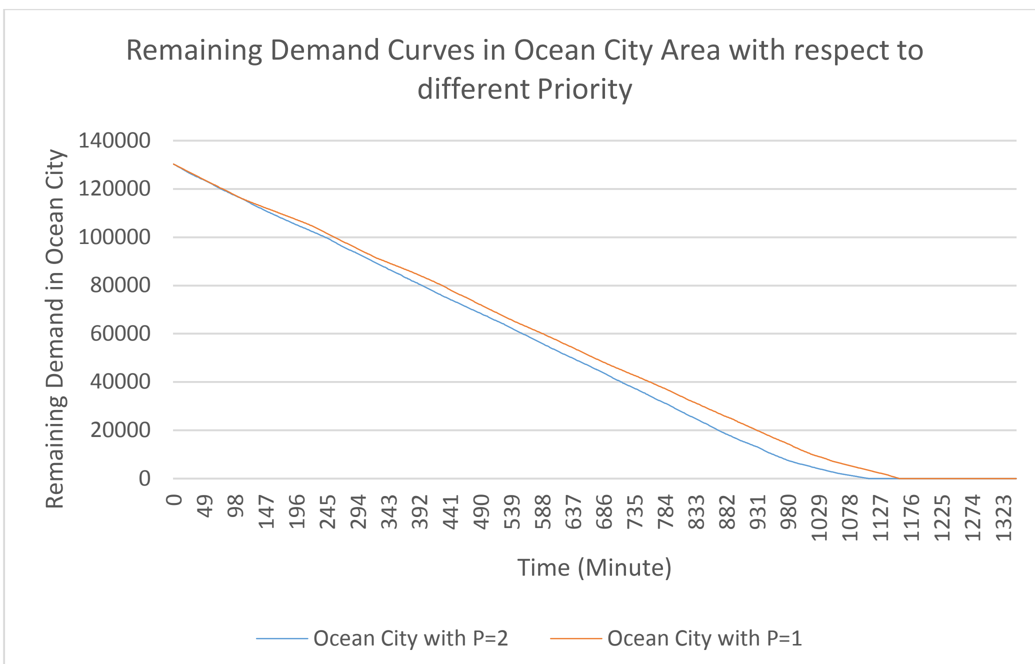


Figure 5-14: Time-dependent Remaining Demand Curves in Ocean City Area with respect to different Priorities

Chapter 6 : Thesis Summary

6.1 Contributions

In this research, a framework for large-scale routing and scheduling optimization was developed for the case of uninterrupted traffic flows. Instead of considering the routing and scheduling in a single problem (using a time-space network), we built the routing and scheduling models separately (i.e. in two phases) so as to enhance the planning efficiency in an urgent real world evacuation scenario. Moreover, the two-phase optimization of the routing and scheduling decision models also provides a high flexibility when using these models. In other words, either the routing optimization model or the scheduling heuristic can be separately adopted for a particular scenario, and they need not be used together. For example, if the evacuation routes have been pre-selected already by some other techniques, then one only needs to use the scheduling heuristic to further determine the demand discharging rate and view the simulation results.

Before demonstrating the optimization models, three significant evacuation performance measures were introduced and derived based on the uninterrupted flow scenario. They are, network clearance time, total travel time and total in-network time. The significance and application of these three performance indicators were discussed and compared. Thereafter the routing and scheduling decision process was formulated as a two-phase optimization framework. In the first phase, a multiple-objective binary programming model with multiple objective functions was formulated. Network clearance time and total in-network time were adopted as the evacuation performance measurements in the routing model. In addition, to better guarantee the a smooth and more effective evacuation process, intersection movement conflicts were eliminated during the optimization process, since conducting the evacuation process based on uninterrupted traffic flow is proved to be more efficient and effective in recent studies. A general mathematical formulation of the intersection conflicts elimination constraints were provided as well. Specifically for the proposed optimization model, a specific iteration-based linear solution approach was developed. The solution approach was tested in the case studies and shown to be effective to give the routing plan with both a minimal network clearance time and total in-network time. In the second phase, a simulation-based scheduling heuristic was developed with the concept from greedy algorithms. This heuristic is able to dynamically determine the discharging rate of each evacuation source with the assistance of an embedded mesoscopic traffic simulator. Meanwhile, the traffic condition of each time interval during the whole evacuation process can also be given from the embedded traffic simulator.

With numerical experiments in the case studies, the proposed optimization framework is proved to be of high optimization capability, as well as high calculation efficiency. In addition, due to the two-phase property of the optimization framework (i.e. considering the routing and scheduling separately), the proposed model is of high flexibility to be used in a real-world scenario. For example, either the routing optimization or the scheduling heuristic can be used separately. Therefore, the overall optimization framework is useful to an emergency-planning agency in their various planning stages for a large-scale evacuation operation.

6.2 Future Research

There are two promising and interesting future research directions related to the work done here:

1) The routing optimization model in this thesis is a binary integer programming model, which aims to determine one or one more evacuation path for each source. However,

there is a limitation of this optimization model. That is, we come up with one or more routes for a specific source by introducing parallel dummy nodes upon this source, but the demand on each parallel dummy node is evenly distributed from the original source during the calculation. Otherwise, if we think the demand of each dummy node as another set of decision variables, the model becomes non-linear both in the constraints and objectives. For example, if we want to find three paths for a source with total demand equal to 3000, we assume each of the three dummy nodes has a demand equal to 1000. Therefore, in the future research, we can investigate how to effectively distribute the original demand among the dummy nodes in order to further mitigate the flow congestion determined by the total demand of each path that has not yet arrived.

2) The main concept of the routing and scheduling optimization model is to maximize the network throughput while avoiding the traffic flow congestion. In other words, making full use of the evacuation network is the core. Therefore, another perspective of viewing that is to firstly consider the routing planning phase with concept of maximal flow minimal cost problem. Thereafter, some network extraction techniques should be used to extract a set of feasible routes from these continuous flows to serve as the optimal evacuation paths. Meanwhile, the demand distribution on each extracted route is obtained as well.

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