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Emergency Evacuation Route Planning Considering Human Behavior During Short- And No-notice Emergency Situations

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EMERGENCY EVACUATION ROUTE PLANNING CONSIDERING HUMAN BEHAVIOR DURING SHORT- AND NO-NOTICE EMERGENCY SITUATIONS

by

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ABSTRACT

Throughout United States and world history, disasters have caused not only significant loss of life, property but also enormous financial loss. The tsunami that occurred on December 26, 2004 is a telling example of the devastation that can occur unexpectedly. This unexpected natural event never happened before in this area. In addition, there was a lack of an emergency response plan for events of that magnitude. Therefore, this event resulted not only in a natural catastrophe for the people of South and Southeast Asia, but it is also considered one of the greatest natural disasters in world history. After the giant wave dissipated, there were more than 230,000 people dead and more than US$10 billion in property damage and loss. Another significant event was the terrorist incident on September 11, 2001 (commonly referred to as 9/11) in United States. This event was unexpected and an unnatural, i.e., man-made event. It resulted in approximately 3,000 lives lost and about US$21 billion in property damage. These and other unexpected (or unanticipated) events give emergency management officials short- or no-notice to prevent or respond to the situation. These and other facts motivate the need for better emergency evacuation route planning (EERP) approaches in order to minimize the loss of human lives and property in short- or no-notice emergency situations.

This research considers aspects of evacuation routing that have received little attention in research and, more importantly, in practice. Previous EERP models only either consider unidirectional evacuee flow from the source of a hazard to destinations of safety or unidirectional emergency first responder flow to the hazard source. However, in real-life emergency situations, these heterogeneous, incompatible flows occur simultaneously over a bi-directional capacitated lane-based travel network, especially in short- and no-notice emergencies. After presenting a review of the work related to the multiple flow EERP

problem, mathematical formulations are presented for the EERP problem where the objective for each problem is to identify an evacuation routing plan (*i.e.*, a traffic flow schedule) that maximizes evacuee and responder flow and minimizes network clearance time of both types of flow. In addition, we integrate the general human response behavior flow pattern, where the cumulative flow behavior follows different degrees of an S-shaped curve depending upon the level of the evacuation order. We extend the analysis to consider potential traffic flow conflicts between the two types of flow under these conditions. A conflict occurs when flow of different types occupy a roadway segment at the same time. Further, with different degrees of flow movement flow for both evacuee and responder flow, the identification of points of flow congestion on the roadway segments that occur within the transportation network is investigated.

Dedicated to my mom and my dad for all their support and encouragement.

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INTRODUCTION

1.1 Background

Throughout United States and world history, disasters have caused not only significant loss of life, property but also enormous financial loss. The tsunami that occurred on December 26, 2004 is a telling example of the devastation that can occur unexpectedly. This unexpected (or unanticipated) natural event never happened before in this area. In addition, there was a lack of an emergency response plan for events of that magnitude. Therefore, this event resulted not only in a natural catastrophe for the people of South and Southeast Asia, but it is also considered one of the greatest natural disasters in world history (NPR 2006). After the giant wave dissipated, there were more than 230,000 people dead and more than US$10 billion in property damage and loss. Another significant event was the terrorist incident on September 11, 2001 (commonly referred to as 9/11) in United States. This event was unexpected and an unnatural, *i.e.*, man-made event. It resulted in approximately 3,000 lives lost and about US$21 billion in property damage. Other major emergency incidents that have occurred in the recent past are summarized in Table 1.1. These and other unexpected events give emergency management officials short or no notice to prevent or respond to the situation.

Table 1.1. Examples of unexpected emergency events (summarized from McBride (2006)).

Event	Location	Lives Lost	Financial Loss (US $)	Month & Year
9/11/2001	New York, Washington, DC and Pennsylvania, USA	2,986	112.5 billion	Sep 2001
Tsunami	South and Southeast Asia	230,000+	10 billion+	Dec 2004
Shadikor (Dam)	Pasni, Quetta, Pakistan	1,000+	15 million +	Feb 2005
Mudslides	Philippines	2,000+	3 million	Feb 2006
Landslides	Central America	1,651+	25 million+	Oct 2006

1.2 Categorization of Emergency Disasters and Events

The Federal Emergency Management Agency (FEMA) provides a taxonomy of disaster and hazard events and categorizes them into three types – man-made, natural and technological (FEMA 2006). The different categories of events are shown in Figure 1.1. We further divide the categories of events by their expectation – expected or unexpected. Unexpected emergency events are those events that give emergency responders short or no advanced notice to react. In other words, the responders have no time or only have a small amount of time to prevent or prepare for the impact of the impending event. Examples of these types of events are tornadoes, earthquakes and even human-caused events such terrorist attacks.

Emergency response to unexpected events is slightly different than that to events that are expected. Those events that are expected, such as hurricanes, wildfires and even civil and international wars, allow more time to prepare for the protection of property and the evacuations of citizens in the targeted areas. In addition, emergency management officials have some *a priori* knowledge about the type of event, the trajectory of the event, scale of the event, and the location of the targeted areas.

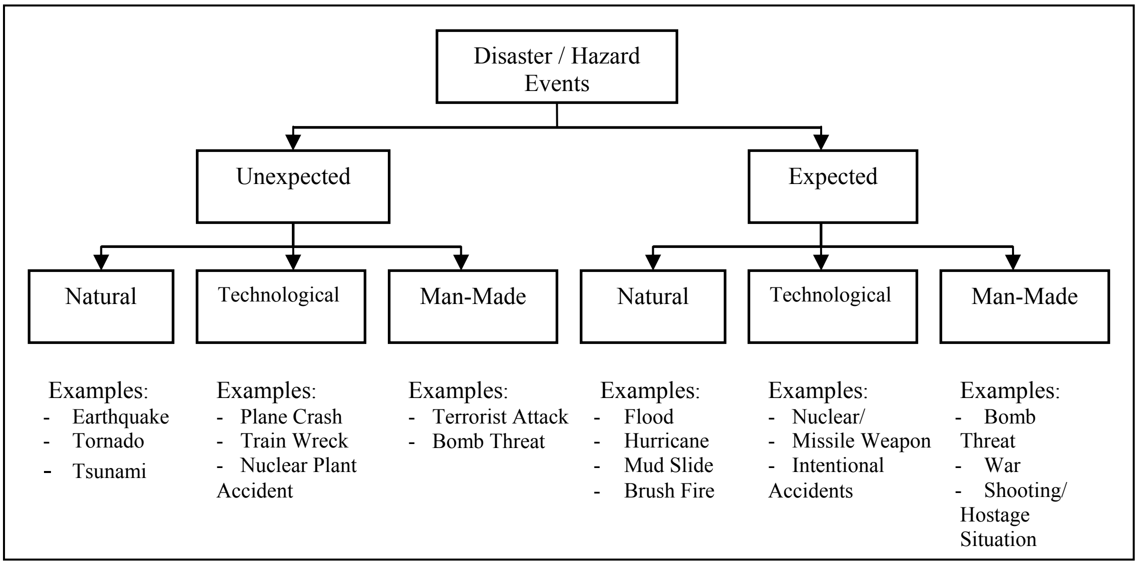


Figure 1.1. Categories of disaster and hazards events (FEMA 2006).

1.3 The Emergency Management Practice

It has long been concluded that the best approach to mitigate the negative impact of disaster events on human life and property is the ability to rapidly generate effective plans to decisively and quickly respond to these disasters. The planning and response action for these events can be classified into five phases (Jain and McLean 2006). These five phases are shown in Figure 1.2.

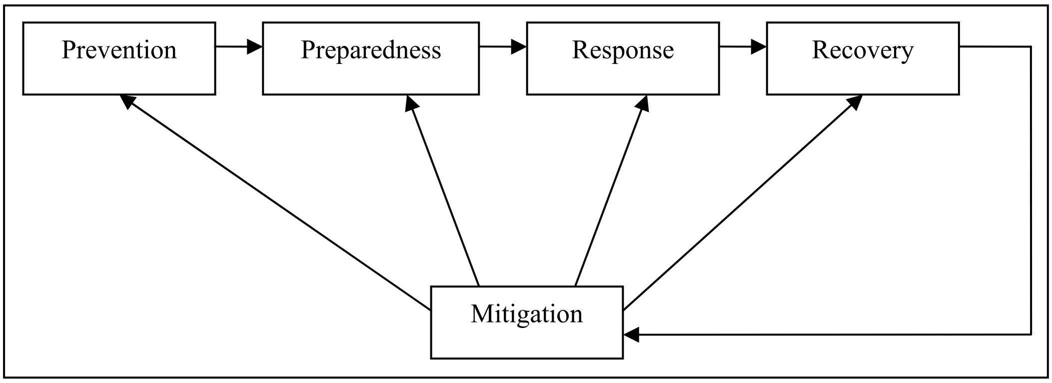


Figure 1.2. Emergency management phases (obtained from Jain and McLean (2006)).

The first phase is *Prevention*. In this phase, the emergency management analyzes, monitors, and detects the possibilities of the disaster causes. Next is the *Preparedness* phase. It involves emergency management officials executing disaster preparation tasks, *e.g.*, installation of early warning systems, preparing and pre-positioning food and medicine and emergency personnel training. Also, the study of the severity of the impact of the disaster event is performed. During the *Response* phase, management gives the proper knowledge and suitable response to victims in the impacted areas. A good response can minimize the consequence of the disaster, which directly impacts the next phase, which is the *Recovery* phase, which involves the activities for restoring the impacted areas to pre-disaster state. This phase can be divided in two sets of recovery plans – short-term plans and long-term plans. Short-term plans are considered the minimum operating plans for the impacted area such as providing temporary housing or shelter and immediate access to water and food. Long-term plans involve among other things long-term financial and property development. It also includes the development of a new emergency planning system. Lastly, the *Mitigation* phase involves post-emergency action where the goal is the elimination or reduction of the effect of similar emergency events. Emergency management agencies can use the results of the efforts from this phase as input and feedback to the other four phases. There is feedback to the Prevention, Preparedness, Response and Recovery phase from the Mitigation Phase in order to design and implement new strategies for future incidents.

In this research, we limit our investigation to the Response phase. In particular, we explore evacuation route planning during unexpected (or unanticipated) emergency incidents. However, we are certain that the results from this exploration will also be relevant to other phases such as the Preparedness phase.

1.4 Human Response Behavior

The understanding and consideration of human behavior in emergency situations is critical when developing emergency response plans, in particular when generating emergency evacuation routes. Individual human response to emergency events can be separated into three general stages (Graat *et al.* 1999). The first stage is when a person receives audio and/or visual cues to warn that an emergency situation has arisen. The second stage is the person's reaction to the warning, which is based on their previous experiences or concerns about the warning. Some people may simply ignore the warning, but others may react immediately to the warning. The last stage of human response occurs after a person acknowledges the emergency event and decides to react to it and then tries to identify the right path to safety. Therefore, the network total clearance time during an evacuation not only considers the actual movement time but also the time that a person recognizes the emergency situation and the time that person takes action to cope with the situation. Au (2006) concludes from previous fire evacuation studies that there are four main factors in human behavior during evacuation. These four factors include, first, the human characteristics, *i.e.* age, gender and experience; second, human response to cue; third, decision-making and, last, the movement. Based on these general stages of human cognition, the cumulative movement of evacuees during emergency situations will generally be slow at the beginning after the start of the emergency period, increase rapidly and then level off towards the end. This behavior generates an S-shaped curve, which has been previously studied from a human cognition point-of-view (*e.g.*, Hanisch *et al*. 2003). Figure 1.3 shows the S-curve that represents the cumulative distribution function for humans moving through time during an emergency. This figure represents the network clearance time. The human movement will start at t_0, and the network clearance time t is divided into k equidistant time intervals Δt (Hanish *et al.* 2003).

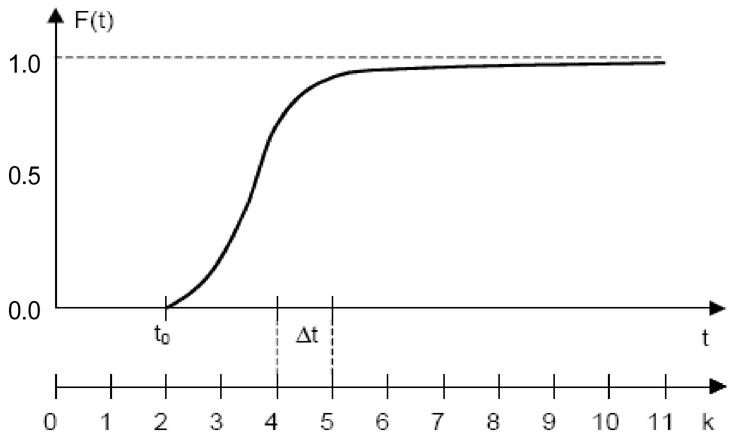


Figure 1.3. Cumulative distribution function of humans moving through time during an emergency (obtained from Hanisch *et al.* (2003)).

The slow movement at the beginning of incident, or pre-movement delay, can result from stress, the unfamiliarity with the situation or hazard area, or the lack of, incomplete or conflicting information needed to make the decision to evacuate. Moreover, the movement is the quantitative perspective and the core information for calculation and design of an evacuation plan.

1.5 Heterogeneous Flows during Short- and No-Notice Emergencies

In addition to considering the behavior of humans during emergency situations, the emergency evacuation routing problem becomes even more challenging when there is more than one type of flow. In this investigation, we explore the real-world case when there are multiple types of heterogeneous flows that are incompatible and they occur simultaneously: evacuee vehicular flow and emergency first responder vehicular flow. By incompatible, we mean that two different types of flow may not occupy a given roadway segment or merge or cross point at the same time. This is quite relevant if safety of the evacuees and responders is a strong concern, which it is. Little work has been done that considers the situation where multiple heterogeneous flows occur during emergency evacuations. A notable exception is the work of Saleh (2008), who considers the situation when contraflow lane reversals are allowed and the objective is to minimize network clearance time of both the evacuees and emergency responders.

We now illustrate the typical flow of these two heterogeneous flows. By applying the human behavior, the evacuee vehicular flow would follow the S-curve as shown in Figure 1.4. On the other hand, emergency first responders can essentially be characterized as a step function. This is because responders are trained to (and must) take immediate action in the event of an emergency situation. However, if there are not enough emergency personnel to handle the incident, a second wave of emergency responders are summoned to support the first wave of responders, creating step function of emergency responder flow. Additional waves of emergency responders are requested depending on the severity of the emergency event.

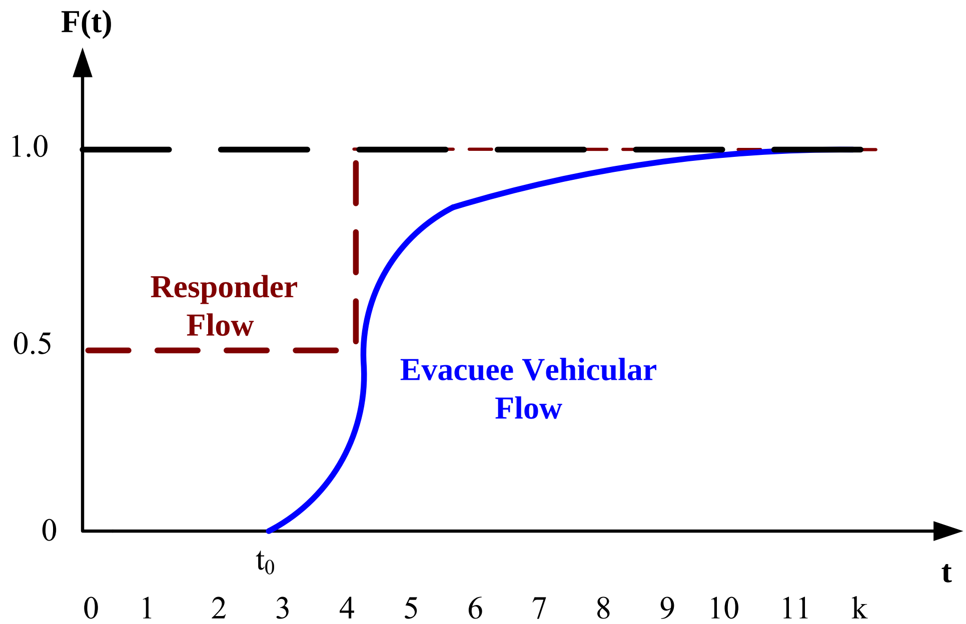


Figure 1.4. Cumulative distribution function for the humans moving through time for evacuee vehicular and emergency first responder flow (adapted from Hanisch *et al.* (2003)).

1.6 Research Objectives

The objectives of this research are as follows. First, we formulate and solve the multiple, heterogeneous, incompatible flow EERP problem for an unexpected emergency event. The focus is on two types of flows: evacuee vehicular and emergency responder vehicular. In the two-flow environment, we:

(1) consider the characteristics of human response behavior patterns during the unexpected emergency events; the cumulative evacuee flow is modeled as the well-studied S-shaped curve, while the emergency responder flow is modeled as a step function representing successive waves of responders;

(2) consider potential conflicts between these two types of flow, where a conflict occurs when flow of different types occupy a roadway segment at the same time; and

(3) identify points of flow congestion on the roadway segments that occur within the transportation network at different levels of human response behavior for both evacuee and responder vehicular flow.

1.7 Expected Contribution of This Research Investigation

This research contributes significantly to the body of research in the area of disaster response and emergency management. As previously discussed, there is a serious need for more effective emergency evacuation route planning methods, especially during those events that are unexpected. To date, there is little work available on the EERP problem where multiple heterogeneous incompatible flows are simultaneously considered.

The primary contribution of this research is that it bolsters efforts to formulate and solve the EERP problem considering multiple heterogeneous flows that occur simultaneously during evacuation. Therefore, this research potentially contributes quite significantly to the body of knowledge in the area of emergency management and disaster planning. In addition, the minimization of traffic conflicts between flows and bottleneck identification in the traffic network will help the emergency management create the better evacuation plans. Lastly, considering the human behavior during the emergency evacuation to the flows should help to emergency managers make reasonable decisions when assigning available resources in traffic network such as emergency personnel and equipment to tasks within the network. Hence, this research should be very valuable not only for short-term emergency response management but also in long-term evacuation planning.

1.8 Organization of This Dissertation

This dissertation is organized as follows. In CHAPTER 2, we provide an overview of the related previous research that examined emergency evacuation route planning. We discuss the specific research gap that this investigation addresses, which includes the consideration of two heterogeneous flows – evacuee vehicular flow and emergency first responder flow. In CHAPTER 3, we present mathematical model formulations for emergency evacuee vehicular flow and first emergency responder flow. Computational results for the single-flow model are also given in this chapter. CHAPTER 4 presents the investigation of traffic flow conflicts between two different types of flow. The model presented in this chapter is a two-flow model formulation. This chapter explores the number of conflicts in the traffic network in the presence of two simultaneous flows. In CHAPTER 5, a roadway bottleneck analysis is presented. Also, the impact of human evacuation response behavior is considered. Lastly, CHAPTER 6 summarizes the research, followed by a discussion of future research directions that extends the work described in this dissertation.

CHAPTER 2:
PREVIOUS RELATED LITERATURE

2.1 Introduction

In this chapter, we discuss the existing literature related to the emergency evacuation route planning problem. First, the general description of the emergency evacuation routing planning problem is given. The network model used to represent the transportation network where consisting of nodes and arcs is described. Second, this chapter explores the previous emergency evacuation route planning (EERP) studies and categorizes them by dividing them into two areas: quantitative approaches and qualitative approaches. Next, the study of human behavior during the emergency events is explored. Last, the remaining potential efforts to improve EERP problem is identified as the research gaps and are investigated in the next chapter.

2.2 The General Emergency Evacuation Routing Planning Problem

Generally, the emergency evacuation route planning (EERP) problem can be described as follows: Let a directed graph $G(\mathbf{N}, \mathbf{A})$ represent the transportation network of the geographic region of interest, where $\mathbf{N}$ is the set of nodes and $\mathbf{A}$ is the set of arcs. The set of nodes $\mathbf{N}$ is divided into three subsets – source (or evacuee origination) nodes $\mathbf{N}_S$, transfer (or intermediate) nodes, $\mathbf{N}_T$ and sink (or safe destination) nodes $\mathbf{N}_D$. Each arc in $\mathbf{A}$ is expressed as (i,j), which is the arc that connects nodes i and j. For each node i, we associate an initial population p_i and a capacity c_i. For each arc, we associate a travel time τ_{ij}, where arc $(i,j) \in \mathbf{A}$, a capacity and a flow direction. The objective is to maximize the flow of people from the hazard source as quickly as possible.

2.3 Emergency Evacuation Routing Planning

A review of the relevant literature indicates that the emergency evacuation route planning problem can be divided into quantitative models and qualitative models, as shown in Figure 2.1.

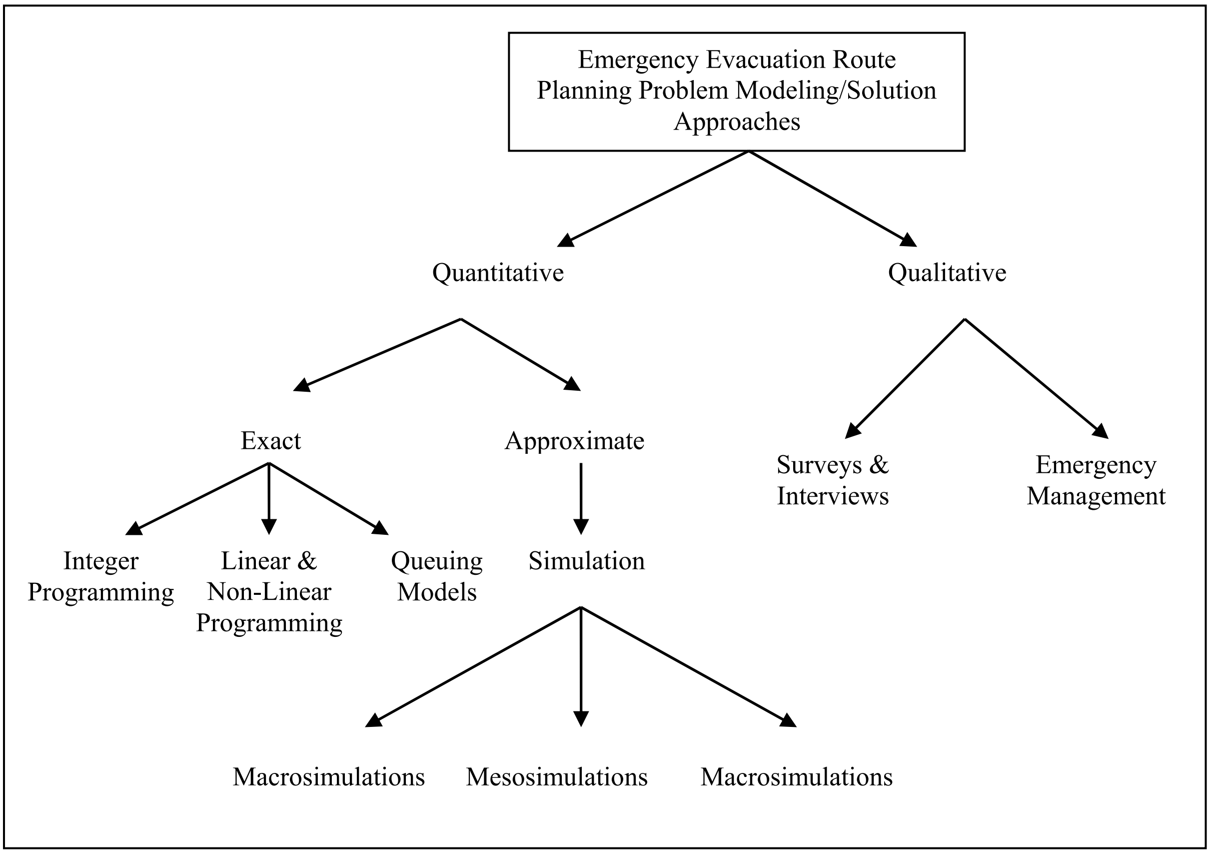


Figure 2.1. Taxonomy of existing emergency evacuation route planning problem modeling approaches.

2.4 Exact Modeling Approaches

2.4.1 Integer, Linear, and Non-Linear Programming Models

The most common approach to model flow in a transportation network is using a network flow diagram consisting of a set of interconnected arcs and nodes (Winston 1994). Network models not only capture the structural relationships between nodes, but they also consider the quantitative characteristics of nodes and arcs such as the length and cost of arc (i,j) between nodes i and j and the node capacities (Elmaghraby 1970).

Elmaghraby (1970) introduces three network modeling approaches. The first is the shortest path approach, which is designed to identify the best individual path. The objective of this modeling approach is to find the optimum (maximum) of the sum of the capacity and time travel ratio. The preferred path is the maximum capacity with the smallest travel time. Various researchers have used a shortest path modeling approach for network routing problems. Avella *et al.* (2002), for instance, use the shortest path approach for medium- and large-scale networks. They propose an extension to the discrete case of the exponential penalty function-based heuristic method for the fast solution of large-scale linear programs. Azaron and Kiafar (2003) model the ship routing problem as a shortest path problem. The weather conditions are the variables that indicate the better route. In addition, weather conditions change over time and these conditions are modeled as a continuous-time Markov chain process. The authors' objective is to find the optimal routing for ship movement in each area.

Another network modeling approach similar to the shortest path model is the minimum cost flow model. These models generally involve minimizing the cost of sending available resources such as labor or materials located at a set of nodes to satisfy the demand at another set of nodes within the network. Yamada (1996) uses the minimum cost flow modeling approach to address the emergency evacuation problem. He uses the distance between the source of an emergency incident and the evacuee shelters as the cost in the network. He then formulates the emergency evacuation problem as a shortest path problem. However, he introduces congestion in the network if the case arises where a large number of the evacuees use the same path to clear the network.

Church and Cova (2000) present a strategy for emergency evacuation routing in a small, yet difficult, area. The authors restrict their analysis to areas that have high population-to-exit capacity ratios. These areas are also known as critical neighborhoods, or critical clusters. They model their problem as a non-linear, constrained optimization problem.

As previously mentioned, the work of Saleh (2008) considers the situation where there are two flows within the network during anticipated, or expected, emergency events. She examines the impact of contraflow lane reversals in which the normal flow directions of lanes on a roadway are reversed in order to increase roadway capacity. She concludes that using contraflow lane reversals reduces network clearance times of both the evacuees and the emergency responders. Saleh's work does not consider the application of her proposed models to evacuation scenarios under short- or no-notice evacuation orders. In addition, she does not consider human evacuation behavior during emergency evacuations, especially in the case where the objective is to minimize conflicts on the roadway segments.

As seen in previous work that formulates the EERP problem using integer, mixed integer programming models and non-linear programming models, researchers assume stationary, steady-state demand flow distributions. In the real-world, the entities such as vehicles and pedestrians have different flow characteristics when responding to emergency situations. Therefore, the collective flow in a transportation network during an emergency situation is not composed of only one type of flow, as assumed in the existing literature.

2.4.2 Queuing Models

There is a stream of research that use queuing theory to model network flow in emergency situations. The work of Larson (1975) is perhaps one of the earliest and most notable. His work focuses on locating district response services such as an ambulance or fire station. This study is based on the $M/M/N$ queuing model and assumes the distribution of service times for every responder is stationary and exponential. Bakuli and Smith (1991) use queuing theory for allocating and resizing resources like passageways in the network to improve the throughput and total egress time. They monitor the occupant service rate in a building corridor where the service rate is a function of velocity σ. The velocity is assumed constant for each occupant, and it depends on number of occupants in the system. The authors formulate an $M/G/C/C$ queuing model with Erlang loss for service rate decay.

Baykal-Gursoy *et al.* (2009) consider space on a roadway as the server for each individual vehicle. They assume the service rate on the roadway decreases when an accident or traffic interruption happens. They formulate an $M/M/C$ queuing model, where there exists a large number of servers C, to model the traffic flow under the interruption incidents, and assume the service process as a Markov model and the service rate is exponentially-distributed. From their experiments, the performance of the $M/M/C$ and $M/M/\infty$ queuing models with service interruptions are very similar, and the relative errors between these two models are acceptable (less than 15%). They conclude that the queuing model $M/M/\infty$ can be used as a valid approximation for the $M/M/C$ model when C is reasonably large. Finally, the authors evaluate their proposed queuing model using a simulation model. They use INTEGRATION traffic simulation software to construct the simulation model. They claim that the results of the $M/M/\infty$ model are comparable to those from the simulation model. However, they note that the simulation approach consumes significant time to run enough replications to reduce the variance.

In summary, even though the researchers above present the benefits from their work, they and others make two, albeit, unrealistic assumptions. First, they assume stationary Poisson arrivals of evacuees to the nodes. Second, heterogeneous flow in the same transportation network is not considered.

2.5 Approximate Modeling Approaches

2.5.1 Simulation Modeling

Over the past two decades, the development of heuristic, or approximate, methods for the emergency evacuation route planning problem has been the focus of most researchers and practitioners, and simulation modeling has been the primary method. Several researchers use macrosimulation in which they model the traffic flow system as a whole, from the aggregate level, and individual entity flow is not modeled, which results in less computational demand (Pidd *et al*. 1996). For example, NETVACI is a traffic macrosimulation model proposed by Sheffi *et al*. (1981). They consider network clearance times during emergency evacuation from the immediate area around nuclear power plants.

The majority of emergency evacuation simulation models are microsimulation models in which all individual vehicles in the road network are tracked. However, this modeling approach requires higher computational demands. Hanisch *et al.* (2003) claim that the entity-based microscopic approach is used often in modeling pedestrian flow. For example, Sinuany-Stern and Stern (1993) conduct a study using microsimulation using SLAM II simulation software. They consider their model a behavioral-based simulation model, where they are concerned with both pedestrian and vehicle evacuation. The authors graphically show the evacuation rate for both pedestrians and vehicles (see Figure 2.2). The authors also claim that the pattern of pedestrian evacuation does not change because the pedestrian flow is independent of the traffic network and does not depend on road capacity. On the other hand, the estimation of vehicle evacuation varies with the following parameters:

1. Traversing time of interaction;
2. Route selection procedure (shortest path versus distance acknowledged from last vehicle);
3. Friction with pedestrians;

4. Time of the evacuation (early-evening versus late-night); and
5. Effect of urban population growth.

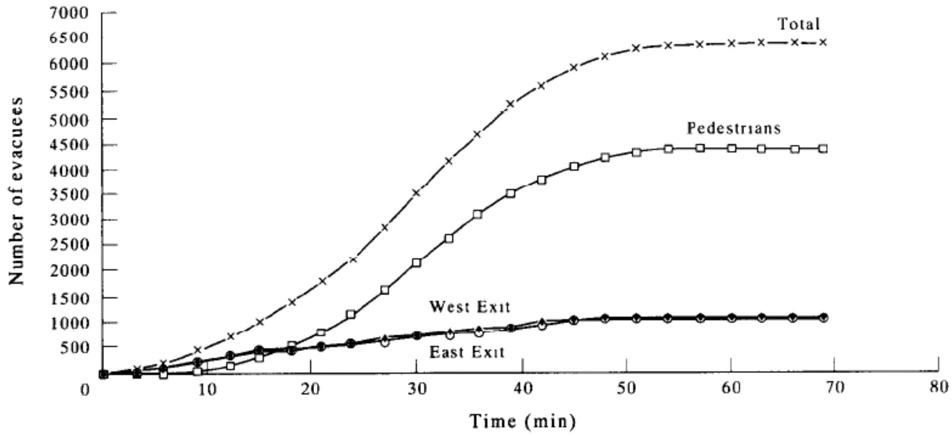


Figure 2.2. Evacuation rate for pedestrians and vehicles (obtained from Sinuany-Stern and Stern (1993)).

Rathi and Solanki (1993) also use microsimulation to compute the network clearance time during emergencies. They use the Oak Ridge Evacuation Modeling System simulation software developed by the Oak Ridge National Laboratory. The researchers divide the emergency area into three zones: (1) Immediate Response Zone, (2) Protective Action Zone and (3) Precautionary Zone. These areas all depend on political, human and topological (connectivity) factors, which are required as input variables in the model.

By using an application of the CORSIM simulation module, Zou *et al.* (2005) customize a model and study the emergency evacuation plan in different scenarios, where the main objective of this study is to compare evacuation plan scenarios. The different inputs or changes that they consider include evacuation duration, route choice and turning proportion at each junction. However, this study shows the result of different scenarios but might not give the final optimal solution in each emergency evacuation plan.

Mollaghasemi and Abdel-Aty (2003) study post-emergency management. Using PARAMICS microsimulation software, they simulate the traffic flow during the emergency event for emergency vehicles instead of the flow of evacuees. The main input variables are similar to other studies in emergency evacuation, which include lane capacities and mean traffic flow.

2.6 Qualitative Modeling Approaches

Some prior studies in emergency management use a qualitative approach to emergency evacuation route planning rather than quantitative methods. These approaches can be divided into three categories: interview, survey and emergency management (planning or documentation).

Fisher *et al.* (1995) study the variables that motivate people to evacuate by conducting interviews with residents from two neighborhoods in Pennsylvania where they previously faced the danger of fire. Then, they construct questionnaires for those neighborhoods to determine what they actually did during the emergency. Fisher *et al*. (1995) conclude that the variables that might increase the probability for residents to move from the emergency areas are "…the clarity of the warning massage, the consistency of the message, the frequency of the warnings, the type of authority giving the message, the accuracy of past warnings and the frequency of the disaster agent".

Hurley-Hanson (2006) address company emergency plans after the tragedy on September 11, 2001. She focuses not only on the aspects the company considers when creating emergency response plans but also on the aspects of employee perceptions of the company's preparedness for such catastrophic situations. There are five main issues that arise: crisis planning and communication, employee safety and security, resilience, descriptive, and losses from the attack. The results from the survey indicate that the responses from companies on the U.S. west coast are quicker than those on the east coast.

From the limited work using qualitative approaches for emergency evacuation route planning, we conclude that qualitative approaches are passive strategies. In other words, the results from surveys and interviews can be used as input for improving the response in the future instead of being used during an actual emergency event. Therefore, these instruments are quite useful in the Mitigation phase of the emergency management phases shown in Figure 1.2.

2.7 Human Response Behavior during Emergencies

Many previous researchers, have studied different aspects of human response behavior during emergency event (*e.g.*, Graat *et al*. 1999, Hanish *et al*. 2003, Lee *et al*. 2004, Furuta and Masahiro 2003, Shendarkar *et al*. 2006). Furuta and Masahiro (2003) study evacuation from an underground mall. They use simulation to analyze not only the physical factors but also the psychological factors and visibility such recognition of exit paths. They conclude that evacuees, who recognize the exit path, will move faster than those who do not. Virtual reality is used by Shendarkar *et al.* (2006) to construct a crowd simulation model during the emergency event. They study crowd behavior under different scenarios. The authors claim that their model can identify the best exit routes and congestion in the network. Cheng *et al.* (2008) present a simulation model for evacuating people from a building. These researchers use Particle Swarm Optimization to model the social characteristics during the evacuation.

In this dissertation, the integer linear programming modeling approach is used to investigate the emergency evacuation route management for the evacuee vehicular flow and emergency responder vehicular flow. In this study, the impact of general human response behavior during emergencies is also explored.

2.8 Summary

The primary focus of this research investigation is emergency evacuation route planning during short- or no-notice emergency events, where the primary objective is to clear the network in the minimum amount of time. Even though this problem has been investigated in the past, there still remain research gaps yet to be addressed. They are the following:

1. *Heterogeneous flow in the traffic networks*. In emergencies, there is not only one type of flow. There are multiple, incompatible flows that occur simultaneously. The first is evacuee vehicular flow. The second is emergency responder flow, which is a generally opposing flow to the evacuee flow. These flows must share a transportation network.
2. *Human Behavior during Emergency Events*. Even though there are many proposed models for emergency evacuation, these models do not include the characteristics of human response behavior. Human behavior can contribute to significantly different movement patterns during an evacuation.

CHAPTER 3:
MATHEMATICAL FORMULATION OF THE EERP PROBLEM

3.1 Introduction

In this chapter, we present mathematical formulations for the emergency evacuation routing problem (EERP) problem. The single-flow evacuation problem, which is typically the focus by researchers either from the evacuee perspective or the emergency responder perspective, is modeled here. In addition, the mathematical model formulation for the two-flow evacuation is also included in this chapter. This model will consider two flows simultaneously in the same travel network. In this case, the evacuee flow moves from the hazard source to destinations of safety, and the second flow is the emergency first responder flow moving towards the hazard source. The model formulation for the single-flow problem is presented first. This single-flow model is the traditional model for the EERP problem. Then, the model formulation for the two-flow problem is presented. We evaluate and discuss the performance of each model using a real-world dataset.

3.2 Single-Flow EERP Problem

In an emergency event, a population of evacuating citizens moves from multiple locations to multiple destinations of safety within the transportation network. Therefore, in the EERP problem, multiple source nodes and multiple sinks must be considered. A dummy node is used to serve as a super source node that feeds the multiple source nodes. In addition, a dummy node is used to serve as a super sink node that receives all flow from the set of sink nodes. Accordingly, the capacities of the super source and super sink nodes are set greater than the total population of citizens within the network. Furthermore, the capacity of the set of arcs emanating from the super source node set of arcs terminating at the super sink node is set to total population size. Finally, the travel time on these arcs is equal to zero.

Now, we present the single-flow emergency evacuation route planning problem. First, we present an integer linear programming model formulation of the single-flow EERP problem. This is similar to the models that currently exist in the literature and is considered the traditional model in this research.

Recall the general formulation of the EERP problem given in CHAPTER 2, where we have a graph $G(\mathbf{N}, \mathbf{A})$ that represents the transportation network $\mathbf{N}$ is the set of nodes, and $\mathbf{A}$ is the set of arcs. There are also, for each node i, an initial population p_i and a capacity v_i. For each arc, there are an associated travel time τ_{ij}, a capacity c_{ij} and a flow direction. The objective is to maximize the flow of people from the hazard source as quickly as possible. The single-flow EERP model can be used to model either the emergency evacuee flow problem or the emergency first responder problem. These problems are viewed as a maximum flow problem and formulated as an integer linear program. The output of the formulation is the allocation of flow volumes to the roadway segments and merge/cross points at each period t during the evacuation. In other words, a schedule is generated that shows the timetable of the evacuation flow through the transportation network. Using notation similar to that used by Shekhar and Kim (2006) and Saleh (2008), the problem parameters, primary and secondary decision variables, objective function and constraints for this model are presented. The primary and, perhaps, the most important difference between the formulation here and that of Saleh (2008) is that the decision variable definition and several modeling assumptions have been corrected in this formulation to sharpen the accuracy and improve clarity of the formulation. For instance, the inclusion of the super source and super sink nodes are not represented in the formulation of Saleh. As a result, the single-flow formulation of Saleh tends to generate misleading results.

Problem Parameters:

T : Desired number of periods to clear the transportation network (user specified);

N : Total number of nodes in the transportation network, *i.e.*, $N = |\mathbf{N}|$;

A : Total number of arcs in the transportation network, *i.e.*, $A = |\mathbf{A}|$;

p_{k0} : Population of people at node k in the transportation network before the active period of the evacuation;

v_k : Capacity of node k in the transportation network;

c_{ij} : Capacity of arc (i,j) in the transportation network; and

τ_{ij} : Travel time on arc (i,j) in the transportation network

Primary Decision Variable:

x_{ijt} : Amount of flow from node i at the beginning of period t (end of period t-1) to node j at the end of period t (beginning of t+1), where $i = 0, \ldots, N+1$; $j = 0, \ldots, N+1$ and $i \neq j$, $t = 1, \ldots, T$.

Secondary Decision Variables:

p_{kt} : Population of people at node k in the transportation network at the end of period t; and

O_t : Number of people that clear the transportation network at end of period t.

Modeling Assumptions:

- There is only one type of flow traveling through the transportation network;
- There is one super source node (Node 0) connecting all flow origination nodes; the capacity of Node 0 is set to infinity, *i.e.*, $v_0 = \infty$;
- The capacity of arc $(0, j)$ ($j = 1, \ldots, N$) in the network is set to infinity, *i.e.*, $c_{0j} = \infty$;

- There is one super sink node (Node N+1) connecting all flow destination nodes; the capacity of Node N+1 is set to infinity, *i.e.*, $v_{N+1} = \infty$;
- The capacity of arc (i, N+1) (i = 1, …, N) in the network is set to infinity, *i.e.*, $c_{i(N+1)} = \infty$;
- The travel time on arc (i,j) τ_{ij} is deterministic and known *a priori* with certainty;
- The travel time on outgoing arc (0, j) (j = 1, …, N) from the super source node is equal to zero, *i.e.*, $\tau_{0j} = 0$ for j = 1, …, N;
- The travel time on incoming arc (i, N+1) to the super sink node is equal to zero, *i.e.*, $\tau_{i(N+1)}$ = 0 for i = 1, …, N; and
- The travel time on a given arc is not a function of the number of entities present on that arc.

$$\text{Max} \quad Z=\sum_{t=1}^{T}\left(T+1-t\right)O_t \tag{3.1}$$

$$\text{s.t.} \quad O_t=\sum_{i=1}^{N-1}x_{iNt} \qquad \forall t = 1, \ldots, T \tag{3.2}$$

$$p_{k1}=p_{k0}-\sum_{j=1}^{N}x_{kj1} \qquad \forall k = 1, \ldots, N;\ k \neq j \tag{3.3}$$

$$p_{kt}=p_{k\left(t-1\right)}-\sum_{j=1}^{N}x_{kjt}+\sum_{i=1}^{N}x_{ik\left(t-\tau_{ik}\right)} \qquad \forall k = 1, \ldots, N;\ k \neq i;\ k \neq j;\ t > 1 \tag{3.4}$$

$$x_{ijt} \leq c_{ij} \qquad \forall i, j = 1, \ldots, N;\ i \neq j;\ \forall t = 1, \ldots, T \tag{3.5}$$

$$p_{kt} \leq v_k \qquad \forall k = 1, \ldots, N;\ \forall t = 1, \ldots, T \tag{3.6}$$

$$x_{ijt} \geq 0, \text{ integer} \qquad \forall i, j = 1, \ldots, N;\ i \neq j;\ \forall t = 1, \ldots, T \tag{3.7}$$

Eq. 3.1 maximizes the number of evacuees exiting the network by making it more desirable to route the evacuees to the final destination node N early during the evacuation interval [1, T] than it is to route them later during the same time interval. Eq. 3.2 represents the total number of evacuees that arrives at the last node, N, from its prior connected node at each time period t. Eqs. 3.3 and 3.4 are the conservation of flow constraints, where Eq. 3.3 represents the conservation of flow during the first time period, and Eq. 3.4 ensures the conservation of flow in the subsequent periods. Eqs. 3.5 and 3.6 are the capacity constraints for arcs and nodes, respectively. Last, Eq. 3.7 represents the non-negativity and integrality constraints.

3.2.1 Solving Single-Flow EERP Problem – A Case Study

The single-flow model is applied to an actual real-world dataset used and generously provided by Shekhar and Kim (2006), which is summarized in APPENDIX A. The real-world data are of the population surrounding a nuclear power plant in Monticello, Minnesota, as shown in Figure 3.1. Shekhar and Kim (2006) report that the demographic data of the dataset are based on Census 2000 population data. These data consist of the population during night-time estimation and employment data during day-time estimation but not including the travel population. The total number of evacuees is 41,950, which is spread throughout the area. In the dataset, there are 47 nodes and 148 travel arcs (shown in Figure 3.2). Each arc and node has a corresponding capacity. For the purposes of our analysis, we modify the network of the area to include a super source node to connect all evacuee origination nodes and a super sink node to connect all evacuee destination nodes. Therefore, in our analysis using this dataset, there are a total of 49 nodes and 152 arcs in the travel network. Furthermore, the travel time in this case study is considered as a deterministic times, and it is not a function of entities on each arc.

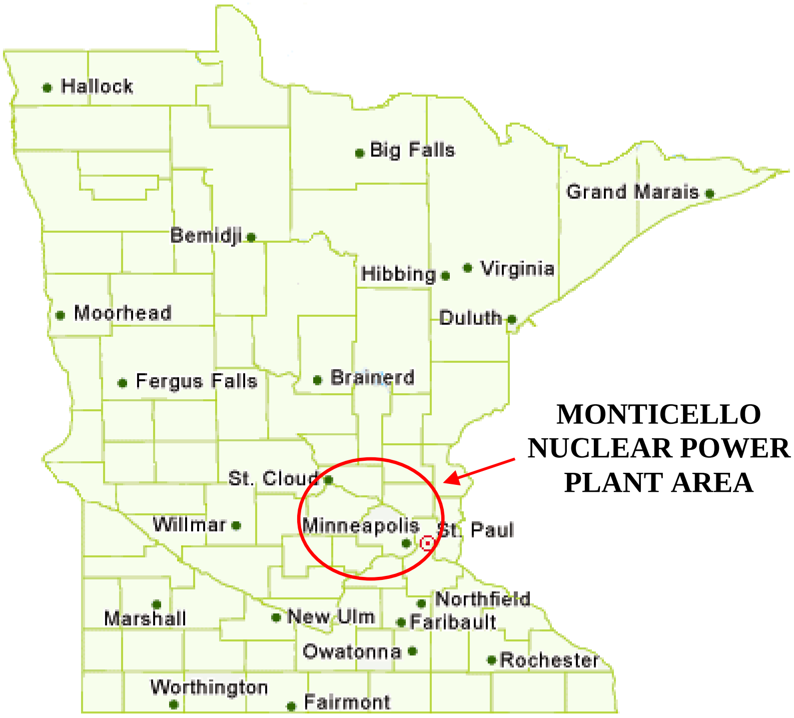


Figure 3.1. Monticello nuclear plant area in Minnesota, USA (image obtained from http://www.registryline.com/foreclosures/minnesota.php).

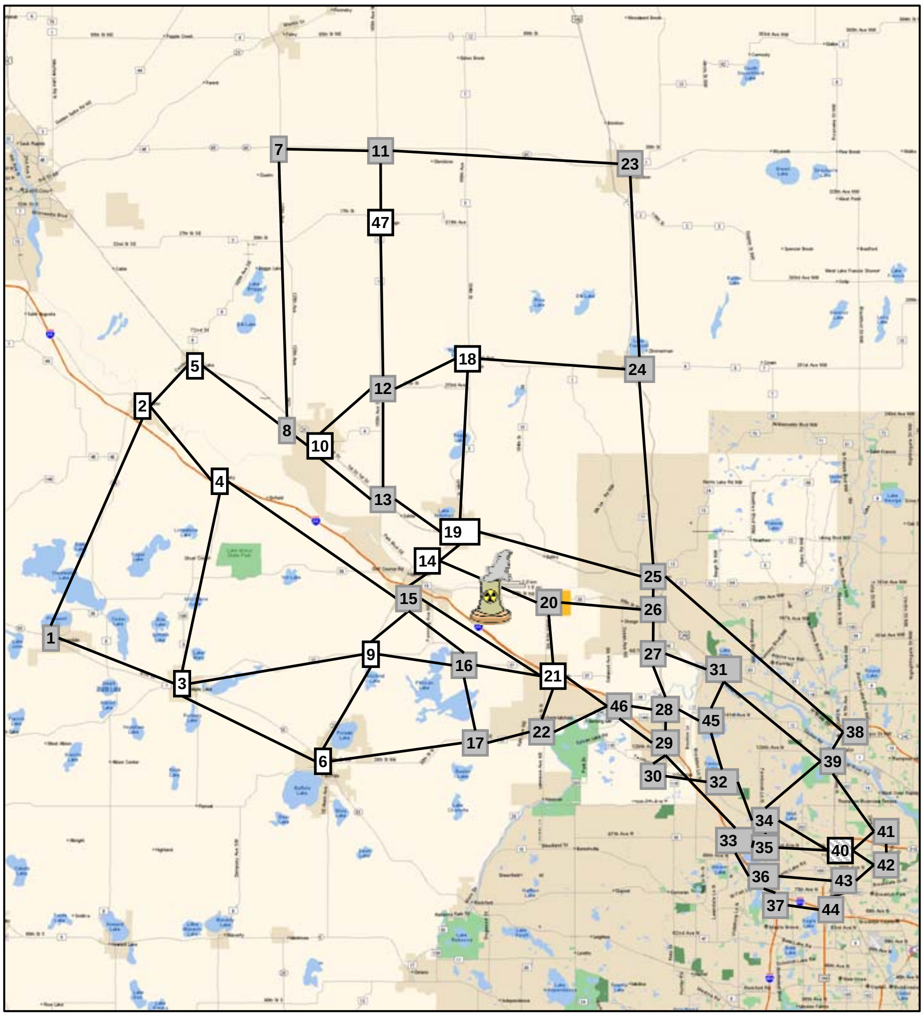


Figure 3.2. Map of the highways and arterials around nuclear power plant in Monticello, Minnesota. The transportation network contains 47 nodes and 148 arcs (Shekhar and Kim 2006).

The response of the single-flow model formulation to changes to flow density is explored. As a result, we expand the original dataset to include three additional levels of emergency evacuee demand *D*, with the total evacuee demand from the original dataset (41,950) as the maximum demand. The four levels of emergency evacuees are shown in Table 3.1. We use the utilization of the network as an indicator of the density within the travel network. In order to determine the network utilization, *U*, we first compute the total network capacity. The total network capacity *NC* is the summation of all network arc capacities and node capacities. In this case study, the network arc capacity can support 22,200 vehicles and the network node capacity can accommodate 52,729 vehicles. So, the total network capacity is 74,929 vehicles. Therefore, network utilization is simply the total demand divided by the network capacity, *i.e.*, $U = D / NC$.

Table 3.1. Level of emergency evacuee demand and network utilization.

Level	Evacuee Demand (Vehicles)	Network Capacity (Vehicles)	Network Utilization
1	27,902	74,929	37%
2	33,832	74,929	45%
3	38,051	74,929	51%
4	41,950	74,929	56%

Continuing with the perspective of single-flow analysis, we investigate the network clearance of a second flow type – the emergency first responders. The flow of emergency first responders is in an opposed direction to the evacuees as the responders move towards the hazard source. First, the Minnesota nuclear power plant dataset is again expanded to include a population of emergency responders. Similar to the evacuee demand, we include three additional levels of emergency first responder demand. The four levels of emergency responder demand and resulting network utilization are shown in Table 3.2. While the Level 4 responder demand may not seem practical in number relative to levels of evacuee demand in Table 3.1, the various levels will show the network under different levels of demand load.

Table 3.2. Level of emergency first responder demand and network utilization.

Level	Responder Demand (Vehicles)	Network Capacity (Vehicles)	Network Utilization
1	1,316	74,929	2%
2	2,618	74,929	3%
3	5,230	74,929	7%
4	10,460	74,929	14%

LINGO 11.0 optimization software by LINDO Systems, Inc. is used to solve the single-flow EERP models to optimality at the different levels of evacuee demand and at the different levels of responder demand. LINGO 11.0 uses a branch-and-bound procedure for

solving integer programming models. The software first evaluates the original model formulation using an integer programming pre-solver. The pre-solver generates constraint cuts using 12 different advanced strategies to reduce the number of variables on which to branch. LINDO Systems reports that the generation of constraint cuts during the pre-solver phase coupled with improved branching rules results in fewer iterations and faster solution times (LINDO Systems 2008).

The performance measure of interest is the network clearance time. Each model is solved on a Pentium 4 1.2 GHz CPU with 2 GB RAM computer. Table 3.3 summarizes the transportation network clearance time for the emergency evacuees as the utilization of the network varies, and Table 3.4 summarizes the network clearance time for the emergency first responders as the utilization of the network varies. From these two tables, the results show the total solver iterations increases as the network density increases.

It can be seen in Figure 3.3 that the network clearance time for the emergency evacuees increases as the demand on the network increases, which makes sense and confirms the results of previous researchers. Similarly, the network clearance time for emergency responders increases as the network density increases, as seen in Figure 3.4.

Table 3.3. Network clearance times for the evacuee single-flow EERP problem.

Level	Evacuee Demand (Vehicles)	Network Utilization	Network Clearance Time	Total Solver Iterations	Solution Time (Minutes)
1	27,902	37%	103	21476	2.55
2	33,832	45%	117	24126	2.58
3	38,051	51%	127	29615	2.70
4	41,950	56%	136	29817	2.70

Table 3.4. Network clearance times for the emergency responder single-flow EERP problem.

Level	Responder Demand (Vehicles)	Network Utilization	Network Clearance Time	Total Solver Iterations	Solution Time (Minutes)
1	1,316	2%	67	6918	2.30
2	2,618	3%	67	8729	2.30
3	5,230	7%	73	13720	2.48
4	10,460	14%	97	12863	2.45

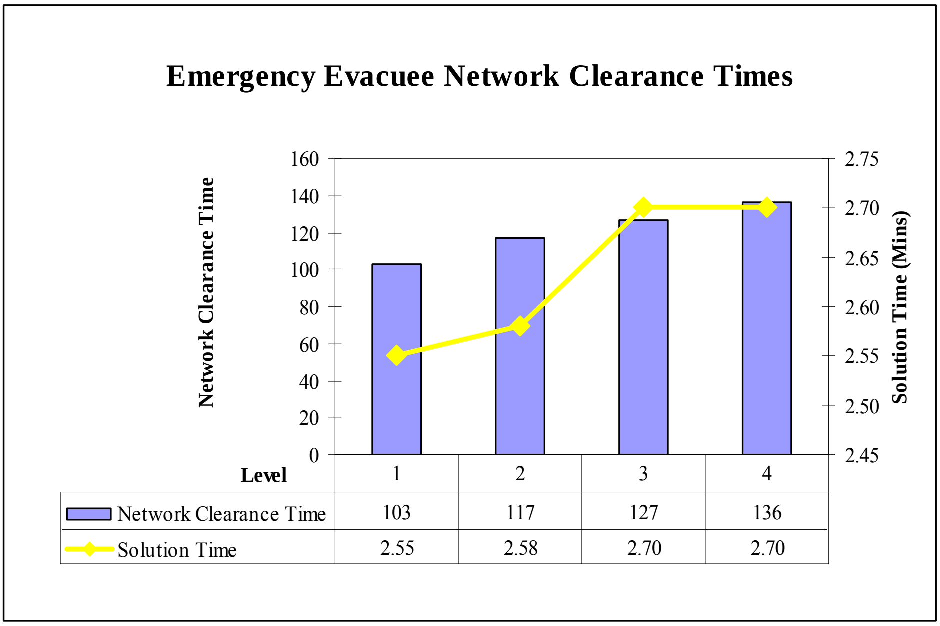


Figure 3.3. Graph of evacuee network clearance times and solution times for the single-flow model for the four evacuee demand levels.

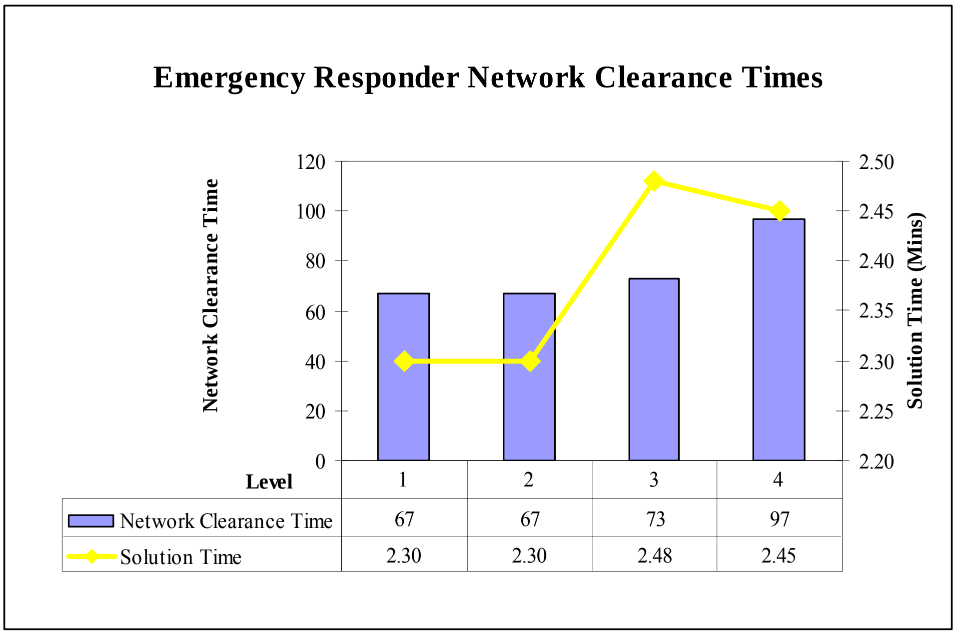


Figure 3.4. Graph of emergency responder network clearance times and associated solution times for the single-flow model for the four responder demand levels.

3.3 Two-Flow EERP Problem

The mathematical formulations for the emergency evacuation route planning problem are presented when two heterogeneous incompatible flows are present in the transportation network. The first flow is the outbound evacuee flow moving from the hazard source to destinations of safety, and the second flow is the inbound emergency first responder flow moving towards the hazard source. The objective is to maximize both the outbound evacuee flow and the inbound responder flow. Similar to the single-flow model formulation presented in Section 3.2, the definitions of the decision variables and some modeling assumptions have been corrected to improve clarity of the two-flow formulation compared to that presented by Saleh (2008). Similar to the single-flow formulation, the output of the two-flow formulation is the allocation of flow volumes to the roadway segments and merge/cross points at each period t during the evacuation of both flow types. We evaluate and discuss the performance of each model using the Monticello, Minnesota dataset.

Problem Parameters:

T : Desired number of periods to clear the transportation network (user-specified);

N : Total number of nodes in the transportation network, *i.e.*, $N = |\mathbf{N}|$;

A : Total number of arcs in the transportation network, *i.e.*, $A = |\mathbf{A}|$;

p_{k0} : Population of evacuees at node k in the network before the active period of the evacuation begins;

w_{k0} : Population of emergency responders at node k in the network before the active period of the evacuation begins;

v_k : Capacity of node k in the network;

c_{ij} : Capacity of arc (i,j) in the network; and

τ_{ij} : Travel time on arc (i,j) in the network

Primary Decision Variables:

x_{ijt} : Evacuee vehicular flow from node i at the beginning of period t (end of period t-1) to node j at the end of period t (beginning of t+1), where $i = 1, \ldots, N$; $j = 1, \ldots, N$ and $i \neq j$, $t = 1, \ldots, T$;

g_{ijt} : Emergency responder flow from node i at the beginning of period t (end of period t+1) to node j at the end of period t (beginning of t+1), where $i = 1, \ldots, N$; $j = 1, \ldots, N$ and $i \neq j$, $t = 1, \ldots, T$;

$$e_{ijt} = \begin{cases} 1, & \text{if evacuee flow exists on arc } (i,j) \text{ during interval } (t, t+\tau_{ij}] \\ 0, & \text{otherwise} \end{cases}$$

$$a_{kt} = \begin{cases} 1, & \text{if evacuee flow exists on node } k \text{ at the end of period } t \\ 0, & \text{otherwise} \end{cases}$$

Secondary Decision Variables:

O_t^e : Number of evacuees vehicles that clear the network at the end of period t;

O_t^r : Number of emergency responder vehicles that clear the network at the end of period t;

p_{kt} : Population of vehicular evacuees at node k where k = 1, ..., N in the transportation network at the end of period t; and

w_{kt} : Population of emergency responders at node k where k = 1,.., N in the transportation network at the end of period t.

Modeling Assumptions:

- There are only two types of flow traveling through the network – evacuee vehicular flow and emergency responder vehicular flow;
- A single network arc cannot be occupied by both evacuee flow and responder flow during the same period of time t;
- A single network node cannot be occupied by both evacuee flow and responder flow during the same period of time t;
- There is one super source node (Node N+1) connecting all evacuee origination nodes and all responder destination nodes;
- There is one super source node (Node 0) connecting all evacuee origination nodes; the capacity of Node 0 is set to infinity, *i.e.*, $v_0 = \infty$;
- The capacity of arc (0, j) (j = 1, …, N) in the network is set to infinity, *i.e.*, $c_{0j} = \infty$;
- There is one super sink node (Node N+1) connecting all flow destination nodes; the capacity of Node N+1 is set to infinity, *i.e.*, $v_{N+1} = \infty$;
- The capacity of arc (i, N+1) (i = 1, …, N) in the network is set to infinity, *i.e.*, $c_{i(N+1)} = \infty$;
- The travel time on a given arc τ_{ij} is deterministic and known *a priori* with certainty;

- The travel time on arc $(0, j)$ ($j = 1, \ldots, N$) exiting the super source node is equal to zero, *i.e.*, $\tau_{0j} = 0$ for $j = 1, \ldots, N$;
- The travel time on arc $(i, N+1)$ ($i = 1, \ldots, N$) entering the super sink node is equal to zero, *i.e.*, $\tau_{i(N+1)} = 0$ for $i = 1, \ldots, N$; and
- The travel time on a given arc is not a function of the number of entities present on that arc

$$\text{Max} \quad Z = \sum_{t=1}^{T} (T+1-t) O_t^e + \sum_{t=1}^{T} (T+1-t) O_t^r \qquad 3.8$$

$$\text{s.t.} \quad O_t^e = \sum_{i=1}^{N-1} x_{iNt} \qquad \forall t = 1, \ldots, T \qquad 3.9$$

$$O_t^r = \sum_{i=N}^{2} g_{i1t} \qquad \forall t = 1, \ldots, T \qquad 3.10$$

$$p_{k1} = p_{k0} - \sum_{j=1}^{N} x_{kj1} \qquad \forall k = 1, \ldots, N;\ k \neq j \qquad 3.11$$

$$p_{kt} = p_{k(t-1)} - \sum_{j=1}^{N} x_{kjt} + \sum_{i=1}^{N} x_{ik(t-\tau_{ik})} \qquad \forall k = 1, \ldots, N;\ k \neq j;\ k \neq i;\ t > 1 \qquad 3.12$$

$$w_{k1} = w_{k0} - \sum_{j=N}^{1} g_{kj1} \qquad \forall k = 1, \ldots, N;\ k \neq j \qquad 3.13$$

$$w_{kt} = w_{k(t-1)} - \sum_{j=N}^{1} g_{kjt} + \sum_{i=N}^{1} g_{ik(t-\tau_{ik})} \qquad \forall k = 1, \ldots, N;\ k \neq j;\ k \neq i;\ t > 1 \qquad 3.14$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} x_{ijt} \leq c_{ij} e_{ijt} \qquad \forall t = 1, \ldots, T;\ i \neq j \qquad 3.15$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} g_{ijt} \leq c_{ij} \left(1 - e_{ijt}\right) \qquad \forall t = 1, \ldots, T;\ i \neq j \qquad 3.16$$

$$p_{kt} \leq v_k a_{kt} \qquad \forall t = 1, \ldots, T;\ \forall k = 1, \ldots, N \qquad 3.17$$

$$w_{kt} \leq v_k (1 - a_{kt}) \qquad \forall t = 1, \ldots, T;\ \forall k = 1, \ldots, N \qquad 3.18$$

Maximizing the flow of evacuees and emergency responders is the main objective in this model, as shown in Eq. 3.8. Eq. 3.9 represents the total number of evacuees who clear the network at the end of period t, and Eq. 3.10 represents the total number of emergency responders who clear the network at the end of period t. Eqs. 3.11 and 3.12 are the conservation of flow constraints for the evacuee flow during the first period and subsequent periods, respectively. The conservation of flow constraints for emergency responder flow are represented by Eqs. 3.13 and 3.14 for first and subsequent periods, respectively. Eq. 3.15 enforces the arc capacity constraint for evacuee flow if the evacuee flow appears on the arc. In the case that emergency responder flow exists on arc (*i,j*), the arc capacity constraint for emergency responder flow will follow Eq. 3.16. In same manner as the arc capacity constraints, the node capacity constraints for evacuee flow and emergency responder flow are represented by Eqs. 3.17 and 3.18, respectively.

3.3.1 Solving Two-Flow EERP Problem – A Case Study

Similar to the single-flow models, the two-flow model is solved using the real-world dataset used by Shekhar and Kim (2006). In this analysis, we evaluate network clearance time of both types of flow. We use the same demand levels as previously given in Table 3.1 and Table 3.2. For convenience, these demand levels are summarized in Table 3.5.

Table 3.5. Level of emergency evacuee demand and emergency first responder demand.

Level	**Evacuee Demand (Vehicles)**	**Responder Demand (Vehicles)**	**Network Capacity (Vehicles)**
1	27,902	1,316	74,929
2	33,832	2,618	74,929
3	38,057	5,230	74,929
4	41,950	10,460	74,929

Similar to the analysis in previous section, we use the utilization of the network U as an indicator of the density within the transportation network for each demand level pair. Therefore, there are a total of 16 possible demand level pairs. The total network capacity and network utilization of each pair is computed and summarized in Table 3.6.

Table 3.6. Two-flow evacuee demand level and emergency responder demand level pairings and associated network utilizations.

Combination	Demand Level Pair (Evacuee Demand Level vs. Responder Demand Level)	Network Utilization
1	Evac Level 1 vs. Resp Level 1	39%
2	Evac Level 1 vs. Resp Level 2	41%
3	Evac Level 1 vs. Resp Level 3	44%
4	Evac Level 1 vs. Resp Level 4	51%
5	Evac Level 2 vs. Resp Level 1	47%
6	Evac Level 2 vs. Resp Level 2	49%
7	Evac Level 2 vs. Resp Level 3	52%
8	Evac Level 2 vs. Resp Level 4	59%
9	Evac Level 3 vs. Resp Level 1	53%
10	Evac Level 3 vs. Resp Level 2	54%
11	Evac Level 3 vs. Resp Level 3	58%
12	Evac Level 3 vs. Resp Level 4	65%
13	Evac Level 4 vs. Resp Level 1	58%
14	Evac Level 4 vs. Resp Level 2	59%
15	Evac Level 4 vs. Resp Level 3	63%
16	Evac Level 4 vs. Resp Level 4	70%

Then, we use LINGO 11.0 to solve the two-flow EERP problem. Within the same transportation network, the arc capacity and node capacity still remain the same. The network clearance time for each type of flow in these combinations does not change. It is likely the case that this result is a result of the particular problem instance, especially in terms of the transportation network demand load. However, the importance of these results still remains that modeling the two flows simultaneously in short- or no-notice emergencies is warranted.

Compared to its single-flow counterpart, the solver iterations and solution time increase dramatically for the two-flow EERP problem. For example, the evacuee demand at Level 3, which contains 38,051 vehicles in the network (51% network utilization), takes 2.42 minutes and 29,615 iterations to compute the answer (shown in Table 3.3). However, the 6th combination demand of emergency evacuee and responder flow (shown in Table 3.7) which contain 36,450 vehicles or 49% of network utilization shows the huge number of computational runtime, 190.72 minutes, and solver iterations, 1318460 iterations to generate the optimal solution.

Table 3.7 Network clearance times for the evacuee and the emergency responder two-flow EERP problem.

Level (Evacuee vs. Responder)	**Network Utilization**	**Network Clearance Time**		**Total Solver Iterations**	**Solution Time (Minutes)**
		Evacuee	Responder		
Level 1 vs. Level 1	39%	103	67	820,968	223.47
Level 1 vs. Level 2	41%	103	67	1,075,664	267.93
Level 1 vs. Level 3	44%	103	73	1,991,844	357.10
Level 1 vs. Level 4	51%	103	97	3,255,335	546.52
Level 2 vs. Level 1	47%	117	67	1,120,874	140.18
Level 2 vs. Level 2	49%	117	67	1,318,460	190.72
Level 2 vs. Level 3	52%	117	73	5,114,865	652.68
Level 2 vs. Level 4	59%	117	97	4,699,134	2564.87
Level 3 vs. Level 1	53%	127	67	1,110,328	153.00
Level 3 vs. Level 2	54%	127	67	3,182,080	236.95
Level 3 vs. Level 3	58%	127	73	1,587,336	253.85
Level 3 vs. Level 4	65%	127	97	3,357,893	1215.60
Level 4 vs. Level 1	58%	136	67	1,440,469	455.72
Level 4 vs. Level 2	59%	136	67	1,681,644	404.07
Level 4 vs. Level 3	63%	136	73	3,487,581	1041.28
Level 4 vs. Level 4	70%	136	97	5,836,624	1847.83

3.4 Summary

Up to this point, the mathematical formulations for both the single- and two-flow analyses are presented and are solved optimally. The single-flow model in this chapter is general and can be found in many studies about emergency evacuation. From the single-flow analysis, it confirms that increasing network utilization increases the network clearance time. However, the solution time in this case is very small.

The two-flow EERP problem corresponds to two types of flows that appear in a transportation network during short- or no-notice emergencies. Invariably, this characteristic makes the model much more complicated and significantly increases the solution time. However, this model still can be used as a base model for further analysis.

Additionally, these experiments verify the idea of considering the heterogeneity of flow during short- or no-notice emergencies. The presented models can strengthen the traditional EERP problem by considering two heterogeneous and incompatible flows that occur during emergency events. However, the results from these two models could be considered as a best case because of no variability such as in queuing or travel time on each arc.

CHAPTER 4:
MINIMIZING ROADWAY CONFLICTS IN THE PRESENCE OF HETEROGENEOUS TRAFFIC FLOWS IN EMERGENCY SITUATIONS

4.1 Introduction

During evacuations, traffic delays and traffic incidents commonly occur, and these traffic delays and incidents may range from the very inconvenient to the quite catastrophic. This is primarily due to the confusion, road unfamiliarity and increased stress levels of those participating in the evacuation. Figure 4.1 shows several traffic incidents that occurred during evacuation in Huntsville, Texas prior to Hurricane Rita's landfall. The confusion and thus the likelihood of traffic accidents increase significantly when multiple flows are present simultaneously on the roadways. Therefore, it is worth pursuing a routing plan that considers not only multiple flow types but also prevents these two flows from occupying the same roadway segments thereby minimizing or eliminating the probability of occurrence of traffic incidents. Rizvi *et al.* (2007) attempt to address this problem of reducing traffic accidents during evacuations; however, their work mainly considers improving the communication among motorists in order to clear the roadway for emergency service vehicles responding to emergencies.


Figure 4.1. Evacuating vehicles in Huntsville, Texas prior to Hurricane Rita's landfall in 2005 (Li 2005).

After extensive review of the open literature, existing EERP models only consider a unidirectional flow, either evacuees moving from a hazard area to areas of safety or emergency responders moving towards hazardous areas. In this chapter, we utilize the two-flow EERP model presented in CHAPTER 3 that simultaneously considers two heterogeneous flows – evacuee flow moving from hazardous area to area of safety, and emergency first responder flow moving towards area of hazard. Generally, the flow of emergency first responders is in an opposed direction to the evacuees as the responders' goal is to move towards the hazard source. There is little previous work done on the EERP problem where both evacuee and responder flows are considered simultaneously, and no work considers the two flows and the minimization of roadway conflicts either on the roadway segments or at the merge and cross points. The chapter will present a study using the model presented in CHAPTER 3 and comparing the results from the traditional model also shown in the previous chapter.

4.2 Previous Related Work

As discussed in CHAPTER 2, several researchers address the EERP problem, and a number of these researchers do consider conflicts on the roadway segments and the merge and cross points (*e.g.*, Poch and Mannering 1996, Rao and Rengaraju 1997, Cova and Johnson 2003). Similar to other researchers that address conflicts at merge and cross points, their objective considers only one type of flow. They attempt to maximize the flow of evacuees from a source to a destination, while minimizing total evacuee travel distance. Sayed and Zein (1999) demonstrate the application of the traffic conflict technique to estimate the traffic safety at intersections. This work considers the traffic under normal traffic conditions (non-emergency event) and they only established the standard for traffic conflict to evaluate the safety in the transportation network instead of finding the proper route in the transportation network. In addition to the conflicts in the transportation network, which might cause the delays and accidents, Baykal-Gürsoy *et al*. (2009) use queuing models to analyze the vehicular traffic flow interrupted by roadway incidents. Zhang *et al*. (2008) consider the importance of safety in traffic network. Even though this work is not quite related to evacuation route planning, the research still shows how to improve the safety performance of highway intersections by using the application of traffic flow theory.

In this chapter, we present formulations for both a single-flow and a two-flow EERP model. The single-flow EERP model considers separately the emergency evacuee flow problem and the emergency first responder problem. We, then, use the formulation of the EERP problem when two heterogeneous flows exist – the more realistic case – especially in short- or no-notice emergencies. In this case, the objective is to maximize both the outbound evacuee flow and the inbound responder flow, while minimizing roadway conflicts. The output of each formulation is the allocation of flow volumes to the roadway segments and merge/cross points at each period t during the evacuation.

4.3 Computational Experiments

Traditionally, emergency planners address the EERP problem either for emergency evacuees or for emergency first responders, but not both simultaneously. Therefore, we solve the model with emergency evacuees and emergency first responders each separately. The results, in fact, are those given in Table 3.3 and Table 3.4, and Table 3.6 summarizes the potential conflicts if the two different flows at the four different levels are in the network at the same time. In other words, each flow is optimized independently of the other, and the resulting evacuation routing plan for each flow type, which identifies the optimal paths and timetable of the flow, is generated. By comparing each arc under each routing plan at each time period t, the number of potential conflicts is recorded. Then, the number of time periods that the evacuees and responders occupy the same arc is recorded. This number represents the routing conflicts that would occur if one type of flow is optimized without considering the other flow. Table 4.1 shows the results of the potential routing conflicts between the two heterogeneous flows. The routing conflicts as a function of network utilization are shown graphically in Figure 4.2. It can be seen that the number of conflicts increases as the demand on the network increases. In the real-world, this increases the potential of unsafe movements by the evacuees and the emergency responders through the network. This strongly suggests that in order to optimize flows while considering the safety of those in the travel network, the movement of the different types of flows must be considered simultaneously.

Table 4.1. Evacuee demand level and emergency responder demand level pairings and routing conflicts under independent optimization.

Level (Evacuee vs. Responder)	**Network Utilization**	**Routing Conflicts**	**Total Solver Iterations**		**Solution Time (Minutes)**	
			Evacuee Only	Responder Only	Evacuee Only	Responder Only
Level 1 vs. Level 1	39%	61	21,476	6,918	2.55	2.30
Level 1 vs. Level 2	41%	68	21,476	8,729	2.55	2.30
Level 1 vs. Level 3	44%	75	21,476	13,720	2.55	2.48
Level 1 vs. Level 4	51%	100	21,476	12,863	2.55	2.45
Level 2 vs. Level 1	47%	59	24,126	6,918	2.58	2.30
Level 2 vs. Level 2	49%	65	24,126	8,729	2.58	2.30
Level 2 vs. Level 3	52%	69	24,126	13,720	2.58	2.48
Level 2 vs. Level 4	59%	100	24,126	12,863	2.58	2.45
Level 3 vs. Level 1	53%	65	29,615	6,918	2.70	2.30
Level 3 vs. Level 2	54%	70	29,615	8,729	2.70	2.30
Level 3 vs. Level 3	58%	82	29,615	13,720	2.70	2.48
Level 3 vs. Level 4	65%	105	29,615	12,863	2.70	2.45
Level 4 vs. Level 1	58%	63	29,817	6,918	2.70	2.30
Level 4 vs. Level 2	59%	66	29,817	8,729	2.70	2.30
Level 4 vs. Level 3	63%	83	29,817	13,720	2.70	2.48
Level 4 vs. Level 4	70%	113	29,817	12,863	2.70	2.45

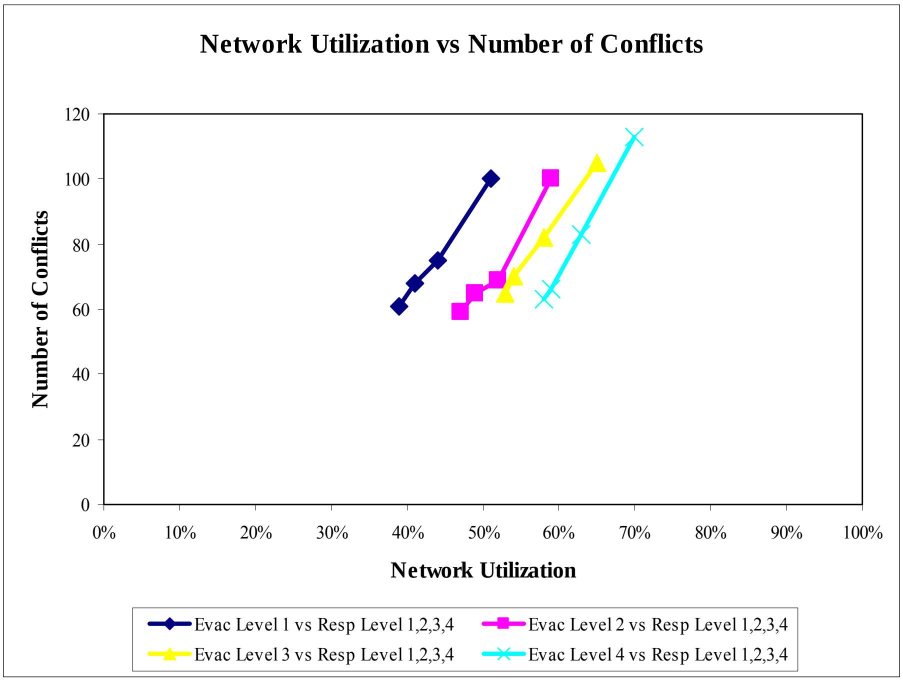


Figure 4.2. Number of routing conflicts for evacuees and emergency responders as a function of utilization.

Next, we solve the two-flow EERP problem with both flows in the network simultaneously. The results from this optimization are shown in Table 4.2. It can be seen that that the proposed two-flow model solves the problem of routing conflicts and there is no degradation in network clearance time for the two flows. However, the required computational time to find the optimal solution for the joint optimization is significantly greater than finding the optimal solution when the two flows are optimized separately.

Table 4.2. Evacuee demand level and emergency responder demand level pairings and routing conflicts under joint optimization.

Level (Evacuee vs. Responder)	**Network Utilization**	**Routing Conflict**	**Network Clearance Time** Evacuee	**Network Clearance Time** Responder	**Solution Time (Minutes)**
Level 1 vs. Level 1	39%	0	103	67	223.47
Level 1 vs. Level 2	41%	0	103	67	267.93
Level 1 vs. Level 3	44%	0	103	73	357.10
Level 1 vs. Level 4	51%	0	103	97	546.52
Level 2 vs. Level 1	47%	0	117	67	140.18
Level 2 vs. Level 2	49%	0	117	67	190.72
Level 2 vs. Level 3	52%	0	117	73	656.68
Level 2 vs. Level 4	59%	0	117	97	2564.87
Level 3 vs. Level 1	53%	0	127	67	153.00
Level 3 vs. Level 2	54%	0	127	67	236.95
Level 3 vs. Level 3	58%	0	127	73	253.85
Level 3 vs. Level 4	65%	0	127	97	1215.60
Level 4 vs. Level 1	58%	0	136	67	455.72
Level 4 vs. Level 2	59%	0	136	67	404.07
Level 4 vs. Level 3	63%	0	136	73	1041.28
Level 4 vs. Level 4	70%	0	136	97	1847.83

4.4 Summary and Usefulness of Results

In the existing literature, emergency evacuee flow and emergency responder flow are typically considered and optimized separately. These models present an incomplete picture that may mislead emergency managers, in particular in the occurrence of potential roadway conflicts. The two-flow EERP model addresses the aspect of roadway conflicts. In fact, the number of roadway conflicts reduces to zero, while the network clearance time remains unchanged. However, the computational time and solver iterations increase quite significantly.

This analysis shows the potential of minimizing the roadway conflicts, where the results not only show the optimal evacuation routes and route scheduling but also eliminate potential roadway conflicts during evacuation. By using the two-flow EERP model, emergency managers can create better evacuation plans and improve the safety during evacuations.

CHAPTER 5:
HUMAN RESPONSE BEHAVIOR AND FLOW MOVEMENT PATTERNS DURING EMERGENCY EVENTS

5.1 Introduction

Many existing models tend to mislead emergency management officials in the implementation of emergency routing plans, especially during short- or no-notice events. This is often due to the fact that human behavior and flow patterns are not considered. To address this gap in the past research, the general human response behavior and flow movement patterns are considered here.

5.2 Characterizing Human Response Behavior during Emergencies

Hanisch *et al*. (2003) states that the general trend of evacuee flow follows an S-shaped curve. This curve shows that evacuees do not all leave the hazard area immediately at the same time. Evacuees may delay their movement at the beginning of evacuation period as explained by Graat *et al*. (1999), who explain three stages of human cognition during an emergency situation. They are:

- *Time to recognize*: the stage that an evacuee receives an emergency warning;
- *Time to cope*: the stage that an evacuee reacts to the emergency situation; and
- *Time to egress*: the stage that an evacuee actually moves and attempts to find the right path to safety.

These three stages of human cognition may cause traffic congestion at unexpected points during the evacuation period, which may lead to more than expected roadway conflicts. So, another dimension of this research analyzes the characteristics of traffic congestion under different evacuation flow patterns.

In this research, the exponential cumulative distribution function is selected to represent the S-curve since it somewhat resembles the human response flow behavior during an emergency evacuation. However, accurately identifying the exact shape and associated parameters of human flow distribution during the different levels of evacuation orders (*i.e.*, voluntary, recommended and mandatory) is important and left for further study. In general, the exponential cumulative distribution function is given by

$$F(x;\lambda) = \begin{cases} 1 - e^{-\lambda x}, & x \geq 0 \\ 0 & , x < 0, \end{cases}$$

where λ is the rate parameter that changes the function's slope. Hence, the value of the rate parameter λ is used to represent different evacuation flow patterns. In this case, λ is set to three different somewhat arbitrary values: 0.2, 0.5 and 1.5 respectively. The exponential cumulative distribution function of these three λ values is shown in Figure 5.1. The λ values limit the amount of flow. As λ increases, so does the amount of flow on the arcs. In addition, these three rate parameter values can represent the evacuation order which each type of evacuation order also shows the different amount of flow. For example, the λ = 0.2 can be considered the flow pattern under a voluntary evacuation order, which means there is a small amount of flow on the arc. The λ = 0.5 is represents the flow pattern under a recommended evacuation order, and λ = 1.5 represents the flow pattern under a mandatory evacuation order.

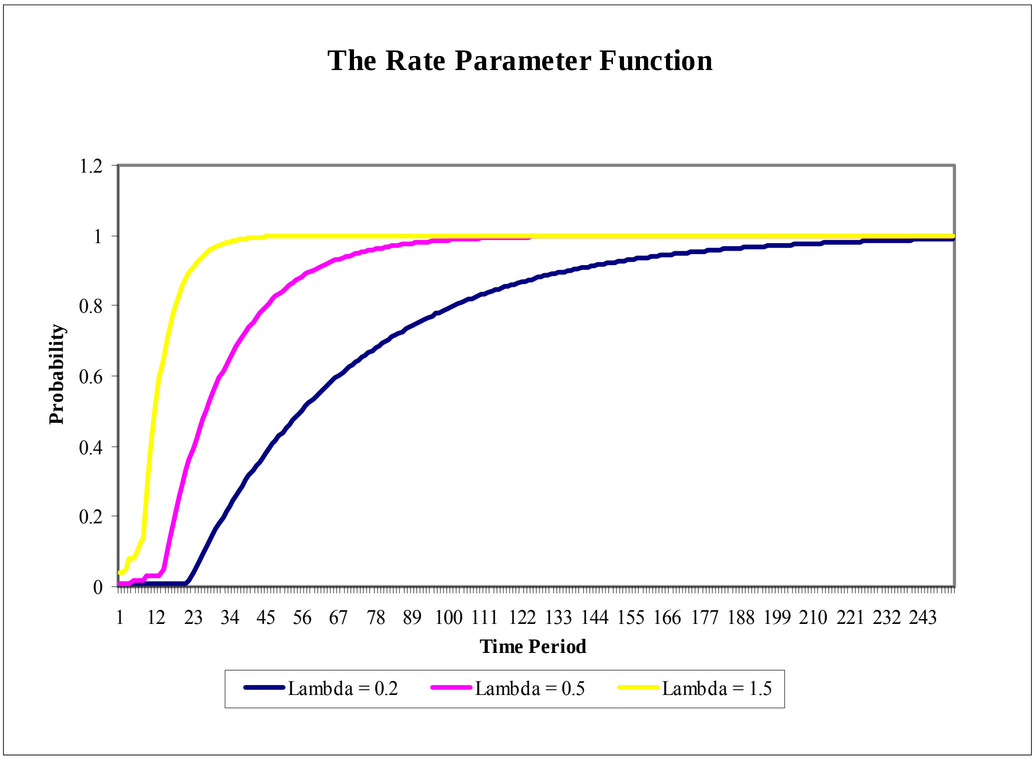


Figure 5.1. The exponential cumulative distribution function at the three λ values.

5.3 Solving Single-Flow EERP Problem Considering Human Response Behavior

By using the same dataset and models presented in CHAPTER 3 and CHAPTER 4, we analyze the impact of human response behavior and flow patterns on network clearance times. The analysis is divided into two cases. First, we explore the situation where only evacuee vehicular flow occupies the transportation network. Second, we consider only emergency responder vehicular flow. As before, the EERP problems are solved using LINGO 11.0, and the performance measure of interest is network clearance time under the human response behavior flow conditions.

5.3.1 Evacuee Flow Considering Human Response Behavior – A Case Study

From the analysis in CHAPTER 4, there are four levels of emergency evacuee demand. These levels and results represent the case when human behavior does not follow an S-curve and all flows move immediately at full capacity. In this section, there are three additional scenarios for each level of evacuee demand. The 12 additional scenarios are as follows:

- Evacuee Demand Level 1 at λ = 0.2, 0.5 and 1.5;
- Evacuee Demand Level 2 at λ = 0.2, 0.5 and 1.5;
- Evacuee Demand Level 3 at λ = 0.2, 0.5 and 1.5; and
- Evacuee Demand Level 4 at λ = 0.2, 0.5 and 1.5.

The network clearance time results for these 12 experiments are summarized in Table 5.1. The network clearance time increases from the case that considers no human response behavior. The reason this occurs is that the evacuee flow needs more time than the previous analysis since not all evacuees move immediately, *i.e.*, a percentage of the evacuees delay their evacuation. When λ = 0.2, the network clearance time increases about 40% when compared to the no human behavior scenario. The results of network clearance time at λ = 0.5 show about a 20% increase at all demand levels, and λ = 1.5 results in about an 8% increase in network clearance time over the no human behavior case. In addition, the solver iterations increase when λ increases.

Table 5.1. Network clearance times for evacuee single-flow EERP with human behavior problem.

$\lambda = 0.2$					
Level	**Evacuee Demand (Number of Vehicles)**	**Network Utilization**	**Network Clearance Time**	**Total Solver Iterations**	**Solution Time (Minutes)**
1	27,902	37%	151	26,362	2.57
2	33,832	45%	166	28,311	2.60
3	38,051	51%	177	29,432	2.67
4	41,950	56%	186	28,048	2.63
$\lambda = 0.5$					
Level	**Evacuee Demand (Number of Vehicles)**	**Network Utilization**	**Network Clearance Time**	**Total Solver Iterations**	**Solution Time (Minutes)**
1	27,902	37%	125	24,212	2.62
2	33,832	45%	139	26,803	2.55
3	38,051	51%	149	27,431	2.65
4	41,950	56%	158	29,712	2.75
$\lambda = 1.5$					
Level	**Evacuee Demand (Number of Vehicles)**	**Network Utilization**	**Network Clearance Time**	**Total Solver Iterations**	**Solution Time (Minutes)**
1	27,902	37%	112	23,318	2.55
2	33,832	45%	127	25,634	2.55
3	38,051	51%	137	27,217	2.68
4	41,950	56%	146	29,273	2.63

The network clearance time versus solution time is shown in Figure 5.2 through Figure 5.5. From these results, they clearly show that the network clearance time increases with respect to λ. In other words, $\lambda = 0.2$ shows the largest impact to the network clearance time followed by $\lambda = 0.5$ and then $\lambda = 1.5$. In other words, the smallest amount of slope makes the highest impact to the network clearance time. The difference of solution time among different demand level is very small. All solution times are in the range of 2.50 to 2.75 minutes.

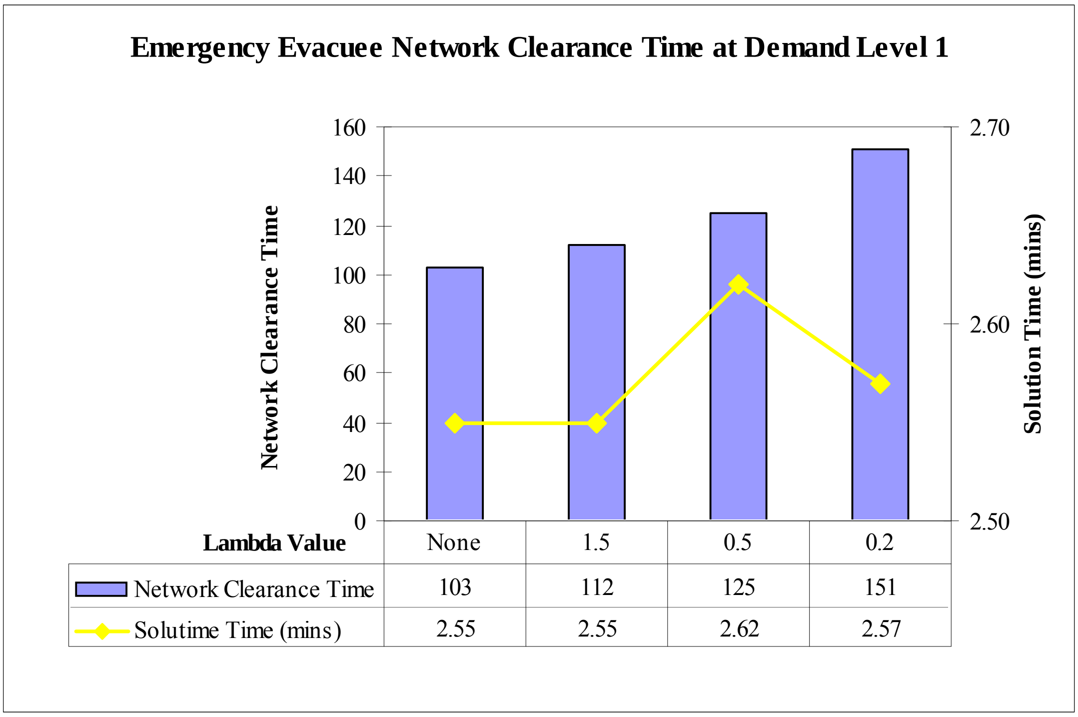


Figure 5.2. Evacuee network clearance times and solution times for the single-flow model at Evacuee Demand Level 1 under the three λ values.

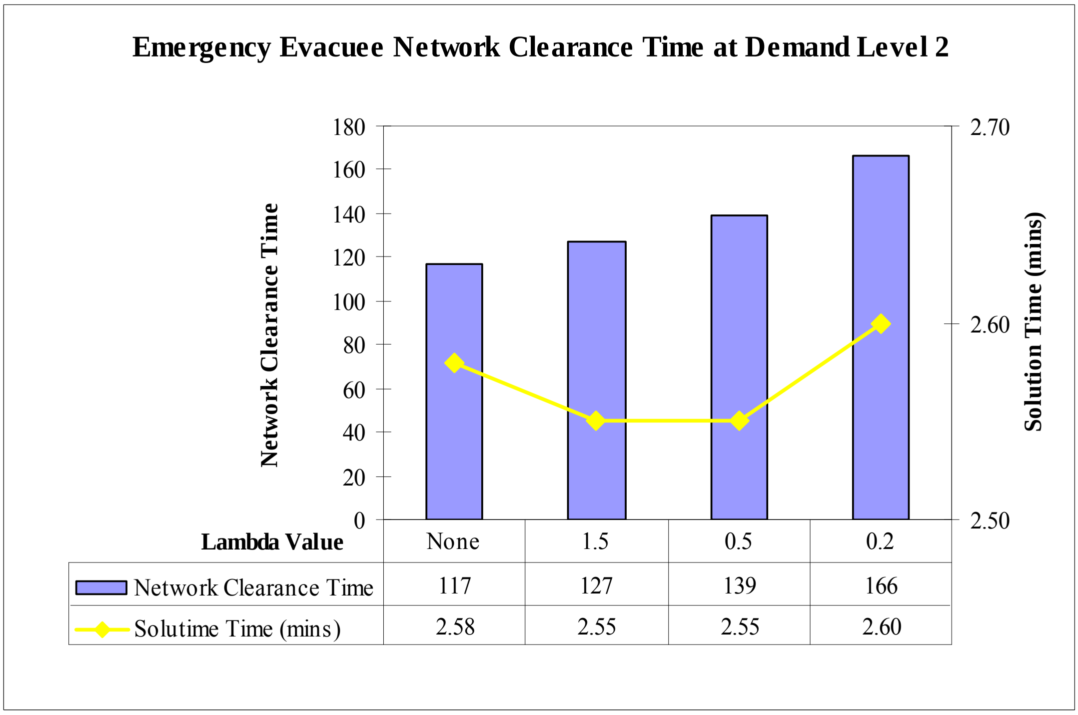


Figure 5.3. Evacuee network clearance times and solution times for the single-flow model at Evacuee Demand Level 2 under the three λ values.

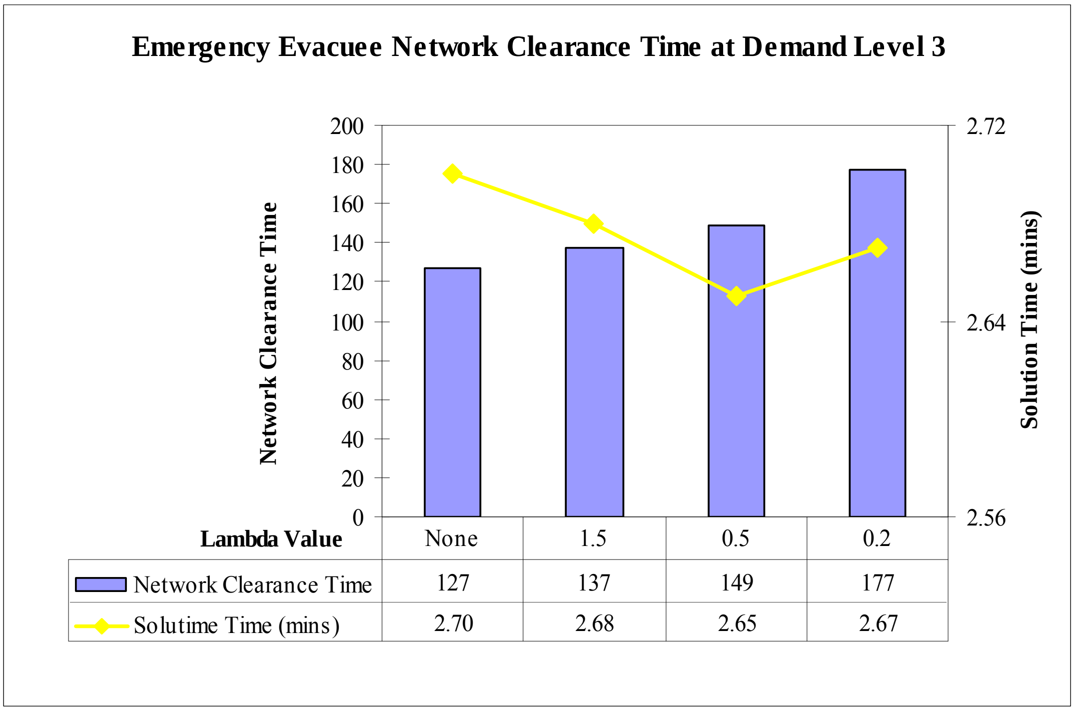


Figure 5.4. Evacuee network clearance times and solution times for the single-flow model at Evacuee Demand Level 3 under the three λ values.

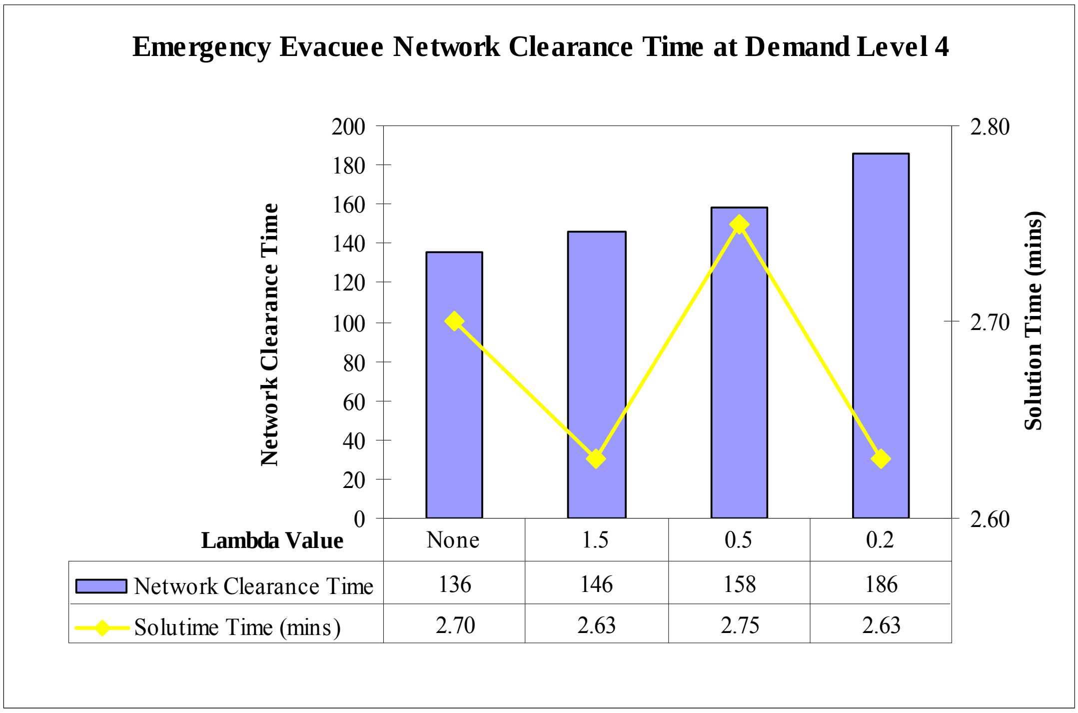


Figure 5.5. Evacuee network clearance times and solution times for the single-flow model at Demand Level 4 under the three λ values.

5.3.2 Emergency Responder Flow Considering Human Response Behavior – A Case Study

In the case of the emergency responders, the analysis uses the same perspective of single-flow analysis for the evacuee flow. When applying the flow movement pattern characteristic of the emergency responder flow to this analysis, a step function is selected to represent this behavior. As discussed in CHAPTER 1, the emergency responders must take immediate action during emergency events. However, the emergency official can set its deployment strategy depending on the severity of the emergency situation. For example, in the case that the first wave of emergency responders cannot handle the incident, another wave of emergency responders is deployed to the hazard area, and so on. Figure 5.6 shows the example of step function used to represent the emergency responder behavior. Three somewhat arbitrary probability (P) values: 0.25, 0.33 and 0.50 are used in this analysis. A P = 0.25 means there are four separate waves of emergency responders that move towards the hazard area. A P = 0.33 means there are three separate waves of emergency responders that move towards the hazard area. A P = 0.50 means there are two separate waves of emergency responders that move towards the hazard area.

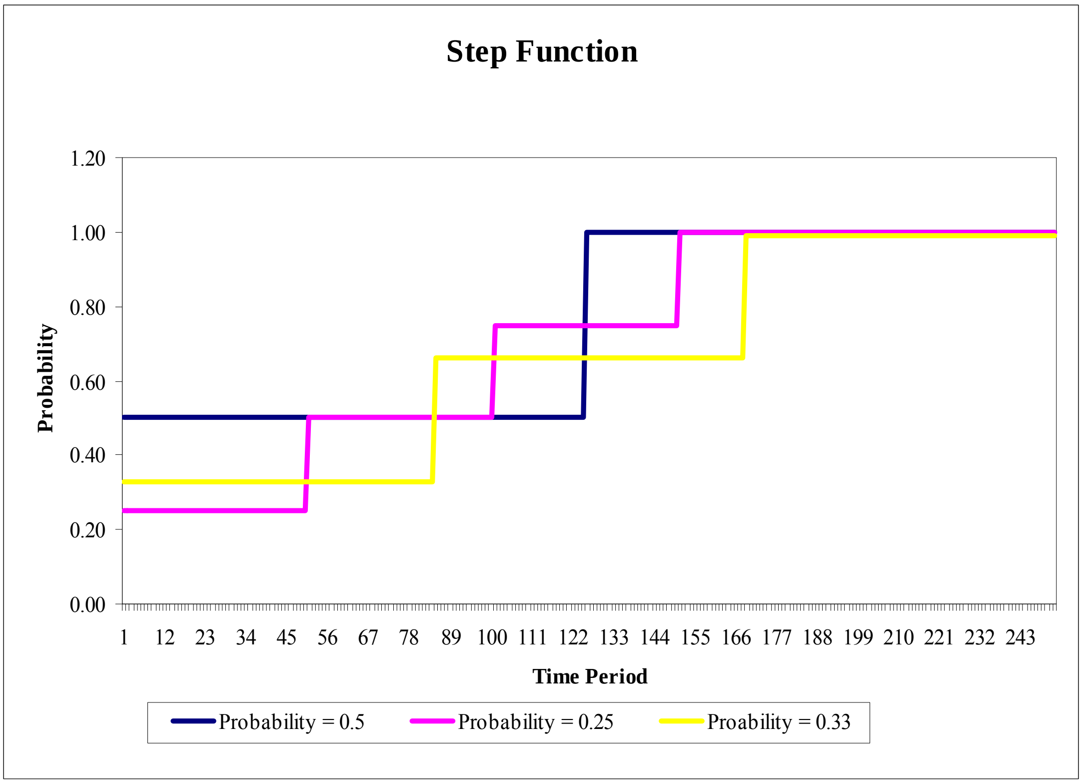


Figure 5.6. The step function that represents emergency responder flow.

The results of this analysis are summarized in Table 5.2. Even though the responder and network utilization in this problem is very low when compared to that of the emergency evacuee case, the results of network clearance time still show the network clearance time increases with respect to the movement probability function except at Demand Level 1. The network clearance time for this level is 67 time units. This is because the total network density of this level is just 2% of the total network capacity. The network clearance time at Emergency Responder Demand Level 2 is increasing 8%, 13%, and 26% for the probability of 0.5, 0.25 and 0.33, respectively, over the no-human behavior case. At Demand Level 3, the network clearance time increases 33%, 37%, and 42% for *P* equal to 0.5, 0.25, and 0.33, respectively. Furthermore, at Emergency Responder Demand Level 4, which has the highest utilization in the model, the network clearance time still increases for the *P*-values of 0.5, 0.25, and 0.33 by 42%, 47%, and 52%, respectively. In terms of solver iterations, the iteration is also increasing by the P-values of 0.5, 0.33, and 0.25, respectively for each responder demand level.

Table 5.2. Network clearance times for the emergency responder single-flow EERP problem at each step function probability P.

P = 0.50					
Level	**Responder Demand (Number of Vehicles)**	**Network Utilization**	**Network Clearance Time**	**Total Solver Iterations**	**Solution Time (Minutes)**
1	1,316	2%	67	8,530	2.30
2	2,618	3%	73	11,134	2.33
3	5,230	7%	97	10,620	2.35
4	10,460	14%	138	14,111	2.35
P = 0.33					
Level	**Responder Demand (Number of Vehicles)**	**Network Utilization**	**Network Clearance Time**	**Total Solver Iterations**	**Solution Time (Minutes)**
1	1,316	2%	67	8,579	2.28
2	2,618	3%	85	9,343	2.28
3	5,230	7%	104	11,663	2.30
4	10,460	14%	148	16,236	2.42
P = 0.25					
Level	**Responder Demand (Number of Vehicles)**	**Network Utilization**	**Network Clearance Time**	**Total Solver Iterations**	**Solution Time (Minutes)**
1	1,316	2%	67	8,785	2.30
2	2,618	3%	76	10,971	2.32
3	5,230	7%	100	12,989	2.33
4	10,460	14%	143	16,884	2.38

Figure 5.7 through Figure 5.10 show the network clearance times for the emergency responder flow increases depending on the P-value of emergency responder flow. However, in the case of emergency responder Demand Level 1, there is no change in the network clearance time. It can be concluded that the probability function of emergency responder movement does not make an impact on the network clearance time for the small amount of demand. Additionally, the solution run times are significantly small and do not increase much from the EERP model with no movement probability.

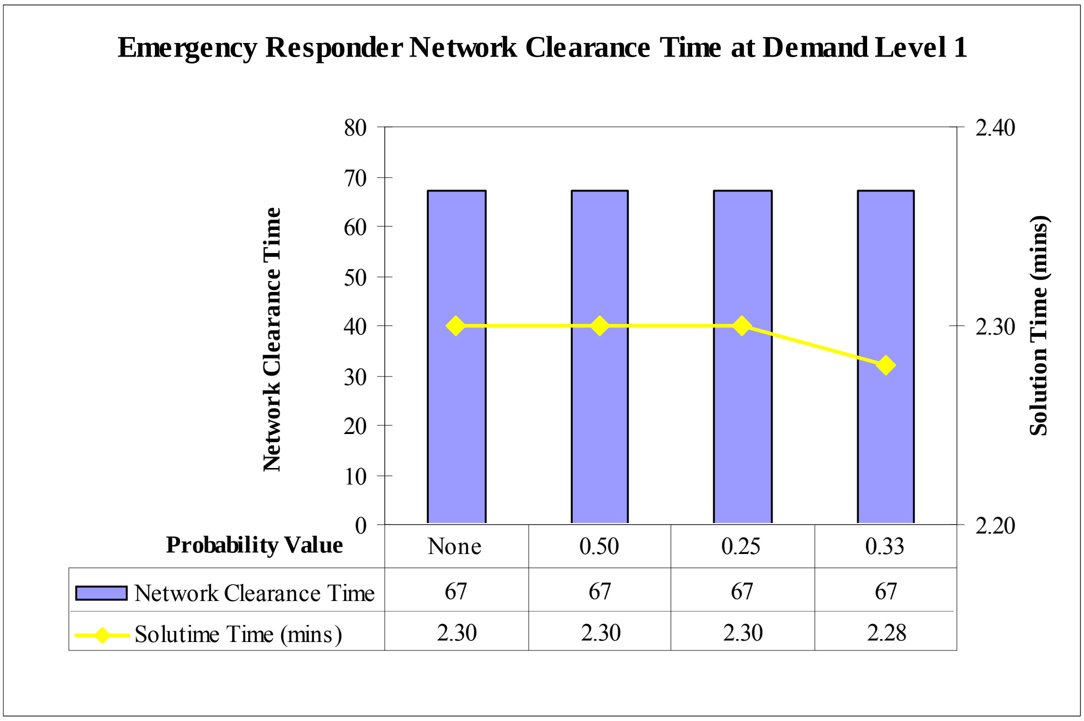


Figure 5.7. Emergency responder network clearance times and solution times for the single-flow model at Responder Demand Level 1 under the three *P* values.

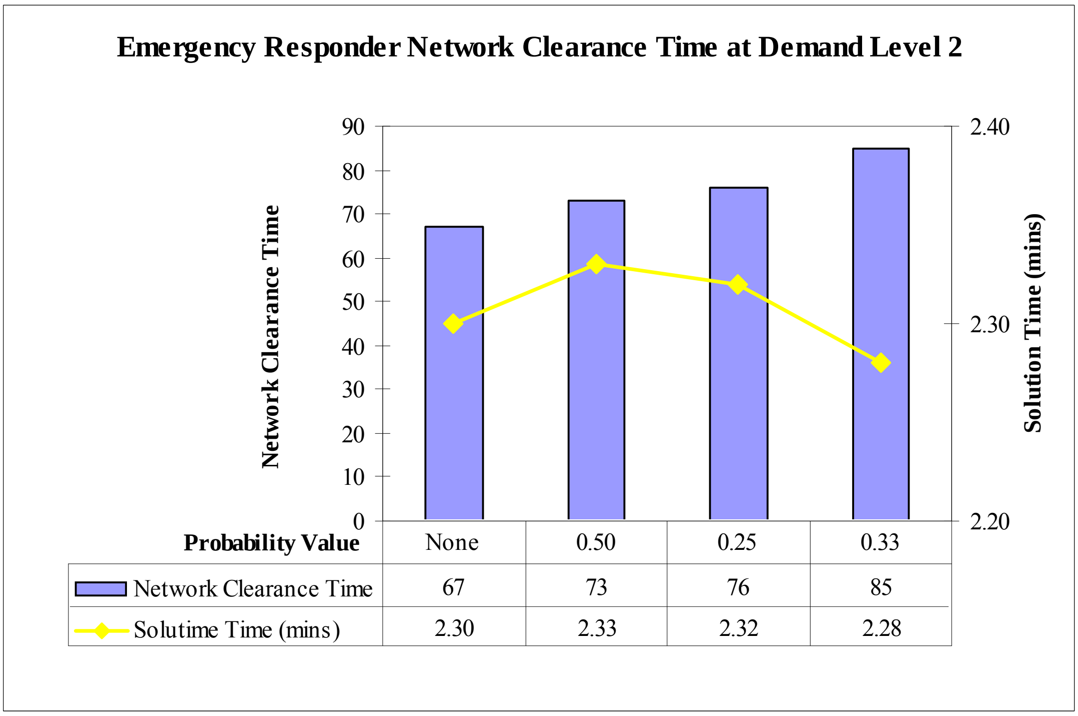


Figure 5.8. Emergency responder network clearance times and solution times for the single-flow model at Responder Demand Level 2 under the three *P* values.

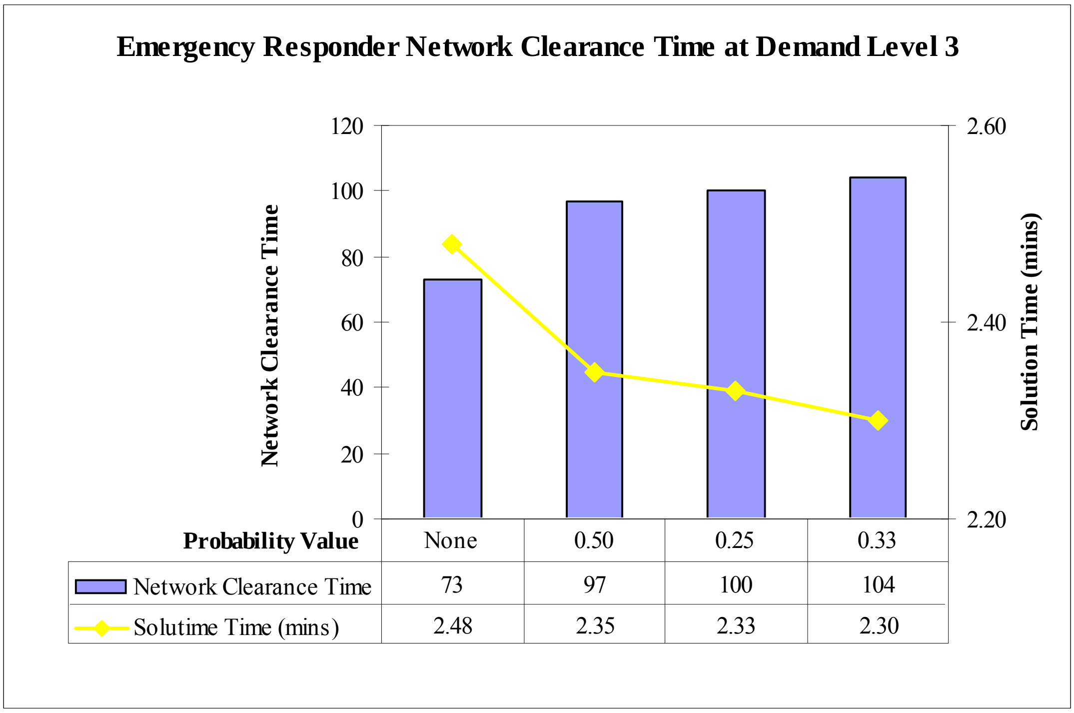


Figure 5.9. Emergency responder network clearance times and solution times for the single-flow model at Responder Demand Level 3 under the three *P* values.

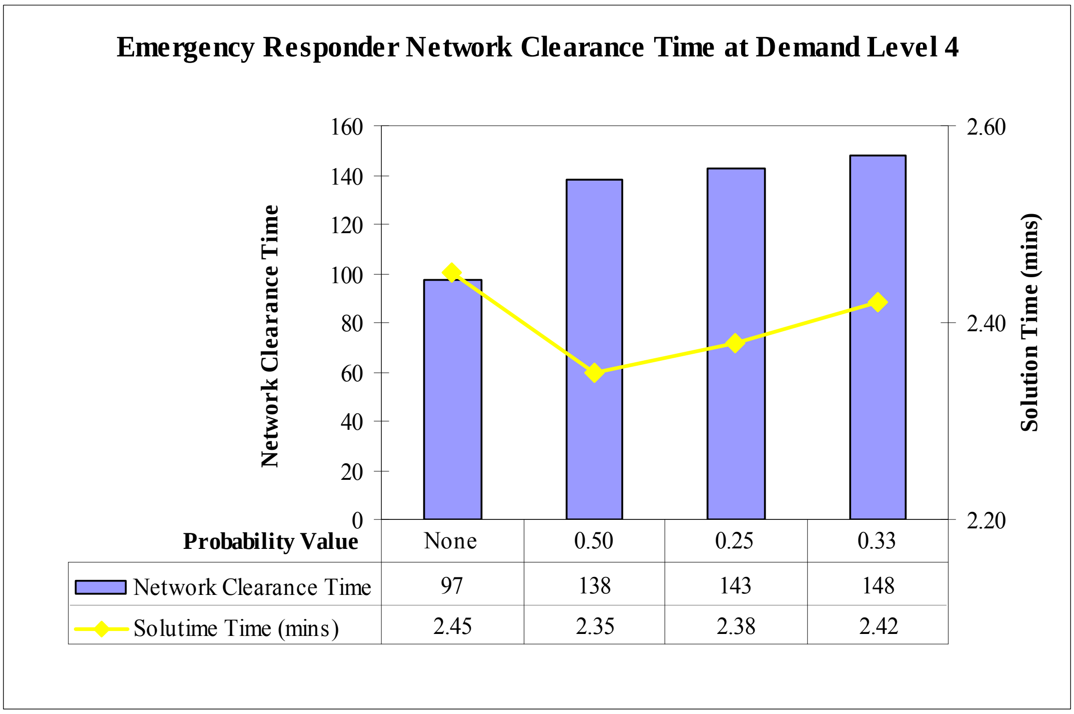


Figure 5.10. Emergency responder network clearance times and solution times for the single-flow model at Responder Demand Level 4 under the three *P* values.

5.4 Impact on Potential Roadway Conflicts

This analysis uses the single-flow EERP model to investigate the effect of human behavior and flow patterns on potential roadway conflicts. Emergency evacuee flow and emergency responder flow are considered separately. The potential routing conflicts for these two flows are summarized in APPENDIX B.

For example, at Evacuee Demand Level 2, where there are 33,832 vehicles, and at each of the four levels of emergency responder demand, the road conflicts of these combinations are shown in Table 5.3. From this result, the probability function gives the same impact of road conflict to the traffic network as the changes in network clearance time. The exponential cumulative distribution function with $\lambda = 0.2$ not only gives the most delay and longest network clearance time, but also generates the highest number of routing conflicts when compared to the rest of exponential cumulative with $\lambda = 0.5$ and 1.5. Conversely, the probability of step function gives a random number of routing conflicts. Regardless, the best factor for routing conflict impact should be the total network clearance time. Longer network clearance times have the most potential to give a higher number of road conflicts in the case that human behavior and movement patterns are applied to the EERP model.

Table 5.3. Routing conflicts under independent optimization for Evacuee Demand Level 2 (33,832 vehicles) and all four emergency responder demand levels under the λ and P value pairings.

Evacuee Demand at 33,832 vehicles vs. Emergency Responder Demand at 1,316 vehicles (*U* = 47%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	28	2.60	2.30
$\lambda = 0.20$ vs. $P = 0.25$	32	2.60	2.28
$\lambda = 0.20$ vs. $P = 0.50$	26	2.60	2.30
$\lambda = 0.50$ vs. $P = 0.33$	17	2.55	2.30
$\lambda = 0.50$ vs. $P = 0.25$	18	2.55	2.28
$\lambda = 0.50$ vs. $P = 0.50$	15	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.33$	9	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.25$	5	2.55	2.28
$\lambda = 1.50$ vs. $P = 0.50$	5	2.55	2.30
Evacuee Demand at 33,832 vehicles vs. Emergency Responder Demand at 2,618 vehicles (*U* = 49%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	47	2.60	2.28
$\lambda = 0.20$ vs. $P = 0.25$	57	2.60	2.32
$\lambda = 0.20$ vs. $P = 0.50$	30	2.60	2.33
$\lambda = 0.50$ vs. $P = 0.33$	26	2.55	2.28
$\lambda = 0.50$ vs. $P = 0.25$	26	2.55	2.32
$\lambda = 0.50$ vs. $P = 0.50$	17	2.55	2.33
$\lambda = 1.50$ vs. $P = 0.33$	10	2.55	2.28
$\lambda = 1.50$ vs. $P = 0.25$	8	2.55	2.32
$\lambda = 1.50$ vs. $P = 0.50$	5	2.55	2.33
Evacuee Demand at 33,832 vehicles vs. Emergency Responder Demand at 5,230 vehicles (*U* = 52%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	55	2.60	2.30
$\lambda = 0.20$ vs. $P = 0.25$	72	2.60	2.33
$\lambda = 0.20$ vs. $P = 0.50$	40	2.60	2.35
$\lambda = 0.50$ vs. $P = 0.33$	35	2.55	2.30
$\lambda = 0.50$ vs. $P = 0.25$	38	2.55	2.33
$\lambda = 0.50$ vs. $P = 0.50$	22	2.55	2.35
$\lambda = 1.50$ vs. $P = 0.33$	19	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.25$	18	2.55	2.33
$\lambda = 1.50$ vs. $P = 0.50$	17	2.55	2.35

Table 5.3. (cont'd). Routing conflicts under independent optimization for Evacuee Demand Level 2 (33,832 vehicles) and all four emergency responder demand levels under the λ and P value pairings.

Evacuee Demand at 33,832 vehicles vs. Emergency Responder Demand at 10,460 vehicles (U = 59%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	114	2.60	2.42
$\lambda = 0.20$ vs. $P = 0.25$	101	2.60	2.38
$\lambda = 0.20$ vs. $P = 0.50$	76	2.60	2.35
$\lambda = 0.50$ vs. $P = 0.33$	89	2.55	2.42
$\lambda = 0.50$ vs. $P = 0.25$	68	2.55	2.38
$\lambda = 0.50$ vs. $P = 0.50$	54	2.55	2.35
$\lambda = 1.50$ vs. $P = 0.33$	100	2.55	2.42
$\lambda = 1.50$ vs. $P = 0.25$	75	2.55	2.38
$\lambda = 1.50$ vs. $P = 0.50$	80	2.55	2.35

Figure 5.11 through Figure 5.14 show the effect of human behavior probability and movement patterns at the Evacuee Demand Level 2 and the Responder Demand Levels 1 to 4. Again, $\lambda = 0.2$ shows the highest impact to the number of routing conflicts when compared to $\lambda = 0.5$ and $\lambda = 1.5$. Evacuee Demand Level 4 and Responder Demand Level 4 is the only case where $\lambda = 1.5$ produces more potential roadway conflicts than $\lambda = 0.5$.

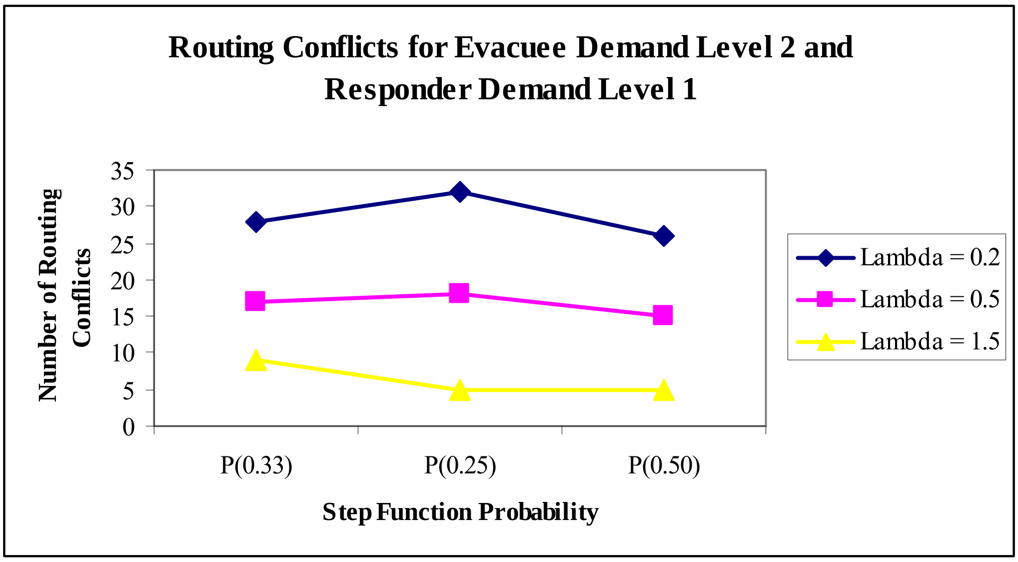


Figure 5.11. Number of routing conflicts considering human response behavior patterns for Evacuee Demand Level 2 and Responder Demand Level 1.

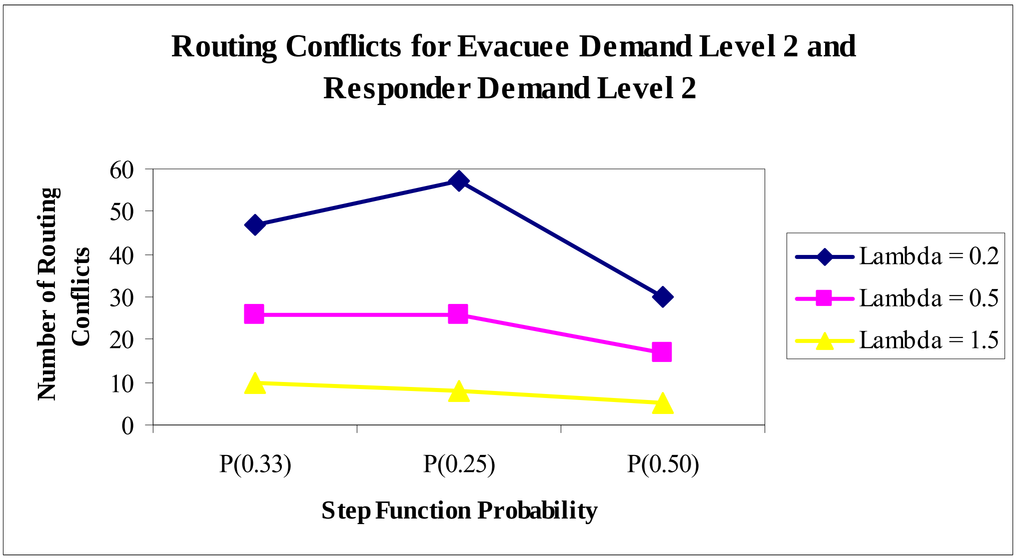


Figure 5.12. Number of routing conflicts considering human response behavior patterns for Evacuee Demand Level 2 and Responder Demand Level 2.

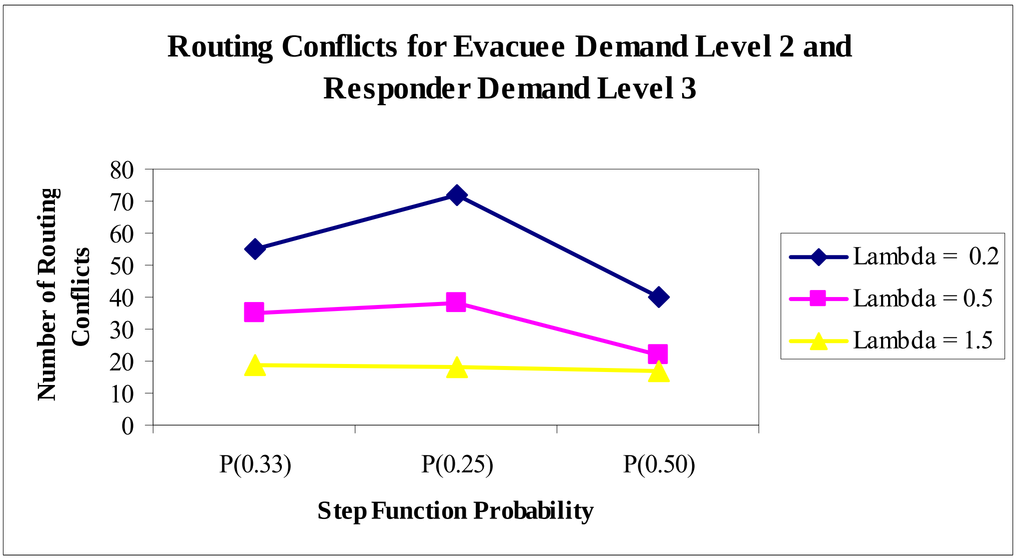


Figure 5.13. Number of routing conflicts considering human response behavior patterns for Evacuee Demand Level 2 and Responder Demand Level 3.

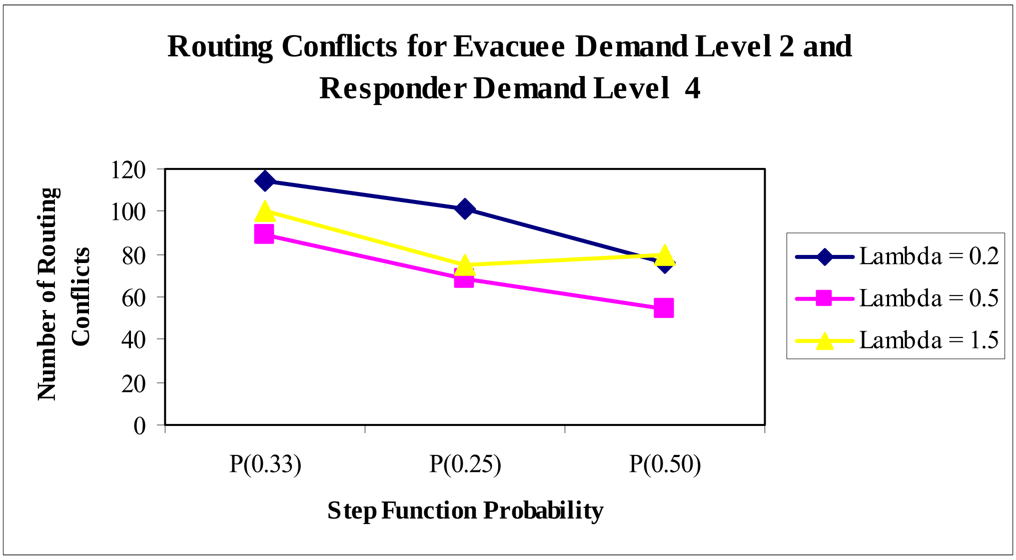


Figure 5.14. Number of routing conflicts considering human response behavior patterns for Evacuee Demand Level 2 and Responder Demand Level 4.

5.5 Analysis of Traffic Bottlenecks under Human Response Behavior Flow Patterns

Due to the high traffic demand during emergency situations, traffic congestion or traffic bottlenecking, often occurs in the transportation network. Wolshon (2006) suggests that the current transportation infrastructure is not built to serve the traffic demand during emergency events or during routine peak periods. The transportation network is designed economically to move populations under normal traffic flow conditions. So, this section will show how the traffic bottleneck in transportation performs during the emergency situation when applying human behavior to the system.

The traffic bottleneck phenomenon can cause another level of difficulty in transportation network. The definition of traffic bottlenecks is given by FHWA (2009) as "A localized section of highway that experiences reduced speeds and inherent delays due to a recurring operational influence or a nonrecurring impacting event." Schrank and Lomax (2007) state that traffic congestion costs Americans about US$63.1 billion per year. This number does not consider the flow during emergency evacuations, which is the main focus in this research, when the traffic network requires quicker movement and has to serve a high number of road users. Throughout the short period of evacuation, the delay decision and disorder are common occurrences. In addition to the high demand in the system, the traffic conflicts analysis in the previous chapter has already shown the significant effect in the traffic system and it will be explored again with the extra focus on human behavior. By exploring these two topics together the emergency management can predict or can have some idea of the conflicts and bottleneck locations so that they might find the better solution and even manage the available resources perfectly.

5.6 Previous Related Work

In general, bottlenecks happen when the demand approaches and exceeds the capacity or performance of the available resources. Researchers study this behavior both in manufacturing and traffic systems.

There are several studies that consider traffic bottlenecking and traffic congestion. For example, Li-ping and Yan (2007) suggests that bottleneck identification is key to traffic safety. They introduce an index formulation to identify the bottleneck and they believe that their management system can be used as a tool for giving the early warning and feedback to the transportation system. Siebel *et al.* (2007) use macroscopic traffic simulation to explore the impact of bottleneck in transportation network in the case of lane reduction and traffic at roadway on-ramps and off-ramps.

Xiao-xiong *et al.* (2006), Pongpibool *et al.* (2007) and Yin *et al.* (2008) use fuzzy-based methods to investigate the traffic bottleneck phenomenon. Xiao-xiong *et al.* (2006) attempt to identify and predict the level of traffic flow. They categorize the traffic flow in three phases: free flow, synchronized flow and wide-moving jam. They use the characteristic parameters such traffic flux, vehicle density and speed to predict the state of the transportation network. Similarly, Yin *et al.* (2008) use a fuzzy clustering model to predict the congestion in network by using the traffic flow, speed and occupancy as the input in their proposed model. Pongpaibool *et al.* (2007) estimate the level of congestion using data from vehicle detection and tracking software to compute the traffic parameters as previous researchers have done and use them as the input in their fuzzy system.

The work of Yamashita *et al*. (2004) supports the idea of information sharing to address traffic congestion. They summarize driver route choice behavior in three categories. The first category is the shortest distance. This is when drivers choose the traffic route by distance and the choice is based on a map only. The second category is the shortest time. This is when drivers make their decision based on the map and traffic congestion information from a traffic information center. The third category is the shortest time route with route information sharing (RIS). With this behavior, drivers make their decision based on the shortest time plus the information of current traffic from RIS such as GPS devices or cell phones. Yamashita *et al*. (2004) run a simulation model with these three behaviors, and the result shows that, in the small network, the decision based on RIS is very efficient. However, within the more complicated network, *i.e*., a radial and ring network, RIS does not result in significant improvement in terms of travel time when compared to the shortest time route behavior.

Other traffic studies focus on traffic under normal conditions and non-emergency situations. For instance, Yueming and Deyun (2008) show how important it is to study the traffic congestion during the emergency evacuations, where their research is to minimize evacuation time. They propose an optimal traffic assignment model based on the shortest emergency evacuation time. With the numerical example, their model can find the optimal route, and the researchers also claim that this model can refer to the real-time traffic conditions to evaluate the new optimal exit. However, this research uses a small dataset, which might not represent the real-world case suitably.

5.6.1 Emergency Evacuee Vehicular Flow - A Case Study

In this case study, the performance measure of interest in this section is the maximum arc utilization. The utilization of an arc at time t is computed by dividing the total entities on that arc at time t by the total capacity of that arc at time t. In this study, the individual capacities of the arcs do not vary over the evacuation period and remain fixed. Maximum arc utilization is the highest utilization achieved by an arc during the active evacuation period.

In the case of the single-flow EERP model with no probability (*i.e.*, no human response behavior effect), most of the arcs along the optimal evacuation paths show a maximum utilization of 100%. This confirms the fact that the evacuees move from the hazard area immediately with no delay. However, when applying human response behavior in the EERP model, the total network clearance increases as described in the previous section; however, the maximum arc utilization in each optimal route decreases. From the results, λ = 0.2 shows the highest impact on the arc utilization, which shows the arc utilization decreases most when compare to other λ values. On the other hand, λ = 1.5 shows the least impact and the maximum arc utilization is very close to the case of the EERP problem with no probability. Looking closely at each arc along the optimal paths, the maximum arc utilization changes over time for the different λ values. Arc 89, which emanates from Node 26 and enters Node 39, is used as an example to explain the impact of human response behavior on arc utilization. The reason that Arc 89 is selected is because this arc shows a high frequency of use, which can be considered as the first evidence of a potential traffic bottleneck. This arc shows a maximum of 100% arc utilization when the human response behavior is not applied to the model. The maximum arc utilization decreases to 99.76% and 93.80% for λ = 0.5 and λ = 0.2, respectively. However, in the case of λ = 1.5, the maximum arc utilization does not change. Another example is Arc 26 (which emanates from Node 9 and enters Node 8). This arc shows a clearer picture of the changing in term of arc utilization. The maximum arc utilizations for no human response behavior on this arc is 100% while 99.94%, 93.61% and 77.69% are the maximum arc utilizations for λ = 1.5, 0.5 and 0.2, respectively. From these results, we can conclude that the arc utilization changes depending upon the different scenarios of human response behavior. Figure 5.15 and Figure 5.16 show the trend of maximum arc utilization under the different cases of human response behavior for Arc 89 and Arc 26, respectively.

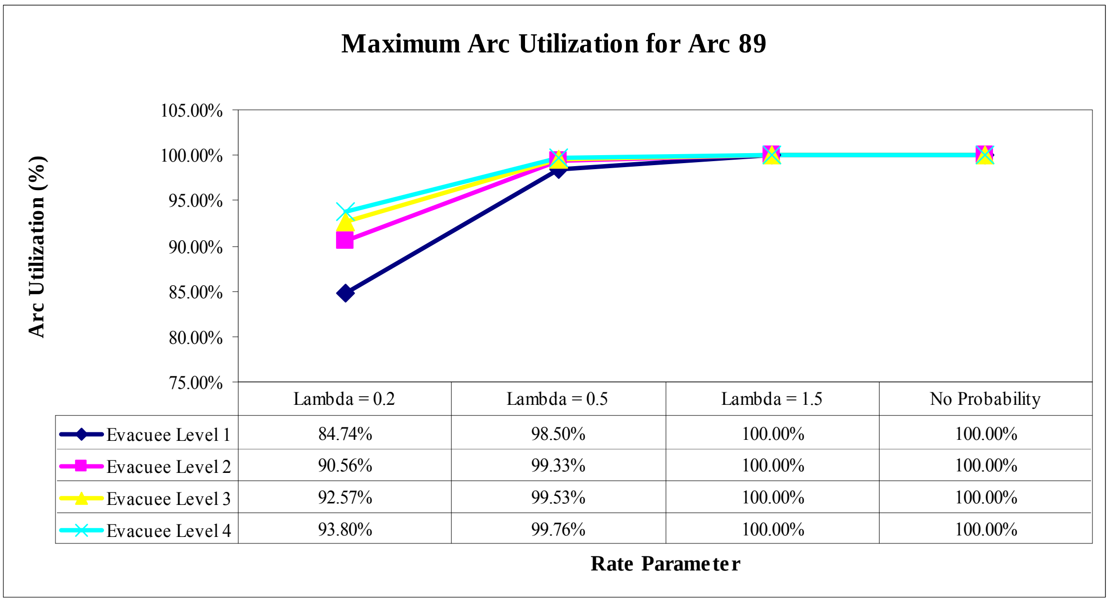


Figure 5.15. The maximum arc utilization for Arc 89 (connecting from Node 28 to Node 39).

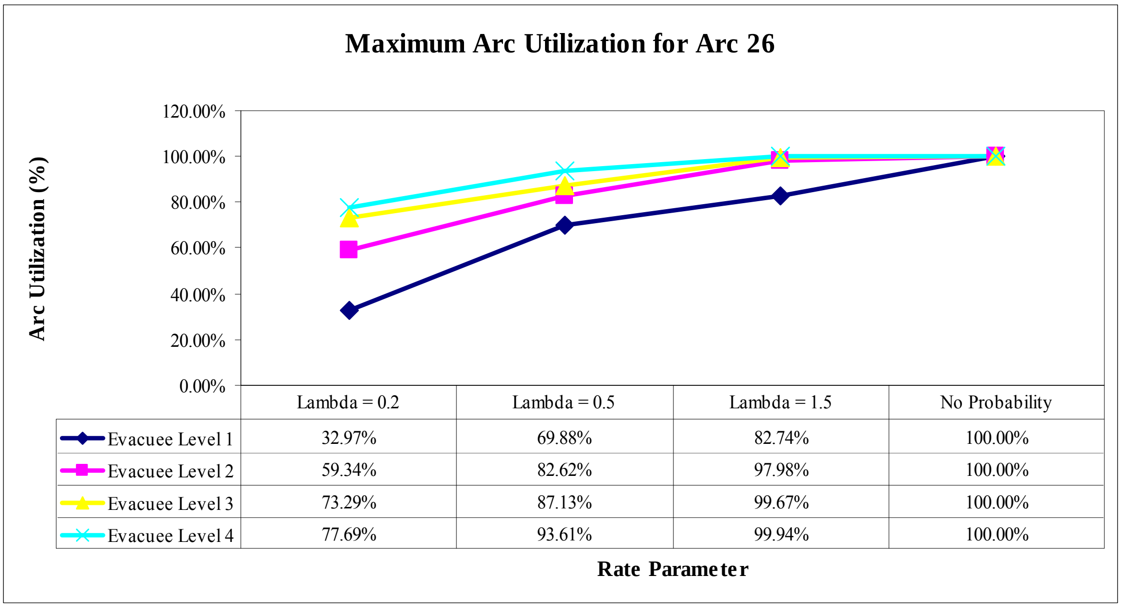


Figure 5.16. The maximum arc utilization for Arc 26 (connecting from Node 9 to Node 8).

Another impact from human response behavior is the shifting of traffic bottleneck. Table 5.4 shows the ranking of the top 40 arcs in terms of maximum arc utilization for Evacuee Demand Level 4, which can be considered for the sake of this study a worst-case scenario since it is the largest evacuee demand. The ranking is in descending order of maximum arc utilization. It can be seen that the arcs do not stay at the same rank position. For example, Arc 89 shifts its position as the rate parameter, λ, changes. In the case of the EERP model with no human response behavior, the Arc 89 (highlighted cell in Table 5.4) has 100% maximum arc utilization, which we can consider it the first potentially troublesome arc to monitor for bottlenecking. However, when the λ = 1.5, 0.5 and 0.2 are applied to the EERP model, the utilization Arc 89 changes. Therefore, its rank position changes 22, 17 and 24, respectively (see Figure 5.17 through Figure 5.20). In other words, the traffic bottleneck tends to shift depending upon the level of evacuation order that is issued.

It can be concluded that the human response behavior not only changes the total network clearance time, but also the arc utilization, which is used as the indicator of potential traffic bottlenecks. Then, with the different human response behavior scenarios, the emergency management can see the potential of traffic bottleneck on each specific arc. As a result, emergency officials can effectively allocate their limited resources to the troublesome locations within the transportation network as they will know which set of roadway and merge and cross points will have the high utilization under different evacuation scenarios.

Table 5.4. The ranking of first 40 maximum arc utilization for the evacuee single-flow EERP problem at Demand Level 4.

Rank Position	No Probability		$\lambda = 0.2$		$\lambda = 0.5$		$\lambda = 1.5$	
	Arc	Max Arc Util	Arc	Max Arc Util	Arc	Max Arc Util	Arc	Max Arc Util
1	3	100.00%	127	96.08%	142	99.92%	142	100.00%
2	6	100.00%	129	96.08%	127	99.92%	119	100.00%
3	7	100.00%	142	96.08%	129	99.92%	127	100.00%
4	9	100.00%	144	96.00%	144	99.91%	129	100.00%
5	11	100.00%	119	95.92%	119	99.91%	144	100.00%
6	13	100.00%	115	95.58%	115	99.89%	115	100.00%
7	15	100.00%	109	95.40%	109	99.87%	145	100.00%
8	17	100.00%	148	95.40%	139	99.86%	109	100.00%
9	19	100.00%	150	95.40%	118	99.84%	139	100.00%
10	21	100.00%	137	95.31%	133	99.83%	133	100.00%
11	23	100.00%	139	95.12%	150	99.83%	137	100.00%
12	26	100.00%	118	94.82%	113	99.82%	118	100.00%
13	27	100.00%	133	94.71%	137	99.82%	99	100.00%
14	29	100.00%	102	94.50%	81	99.80%	148	100.00%
15	30	100.00%	113	94.50%	148	99.80%	81	100.00%
16	31	100.00%	99	94.27%	95	99.78%	105	100.00%
17	33	100.00%	108	94.16%	89	99.76%	95	100.00%
18	35	100.00%	95	94.04%	103	99.76%	108	100.00%
19	37	100.00%	105	94.04%	108	99.75%	113	100.00%
20	39	100.00%	81	93.92%	87	99.70%	150	100.00%
21	41	100.00%	91	93.92%	91	99.70%	123	100.00%
22	42	100.00%	93	93.92%	105	99.70%	89	100.00%
23	44	100.00%	97	93.92%	99	99.67%	146	100.00%
24	45	100.00%	89	93.80%	126	99.67%	124	100.00%
25	47	100.00%	88	93.67%	65	99.65%	87	100.00%
26	48	100.00%	77	93.41%	102	99.59%	91	100.00%
27	49	100.00%	126	93.28%	111	99.57%	65	100.00%
28	51	100.00%	65	92.86%	59	99.55%	121	100.00%
29	52	100.00%	75	92.86%	77	99.53%	79	100.00%
30	53	100.00%	63	92.27%	131	99.53%	77	100.00%
31	54	100.00%	23	92.11%	88	99.50%	93	100.00%
32	55	100.00%	55	91.46%	23	99.48%	126	100.00%
33	57	100.00%	73	91.46%	33	99.48%	71	100.00%
34	58	100.00%	52	91.11%	63	99.48%	23	100.00%
35	59	100.00%	79	90.93%	85	99.48%	85	100.00%
36	61	100.00%	61	90.74%	79	99.45%	103	100.00%
37	62	100.00%	71	90.74%	71	99.39%	59	100.00%
38	63	100.00%	33	90.37%	75	99.36%	73	100.00%
39	64	100.00%	53	90.37%	74	99.33%	102	100.00%
40	65	100.00%	62	90.17%	49	99.22%	111	100.00%

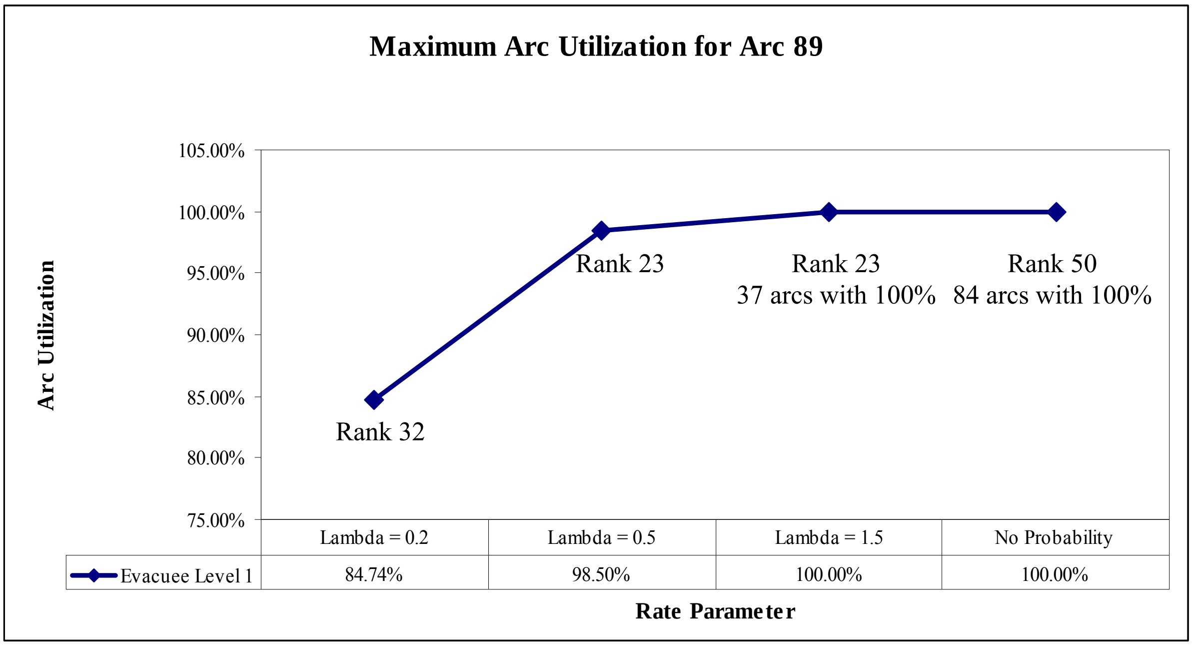


Figure 5.17. The maximum arc utilization for Arc 89 at Evacuee Demand Level 1.

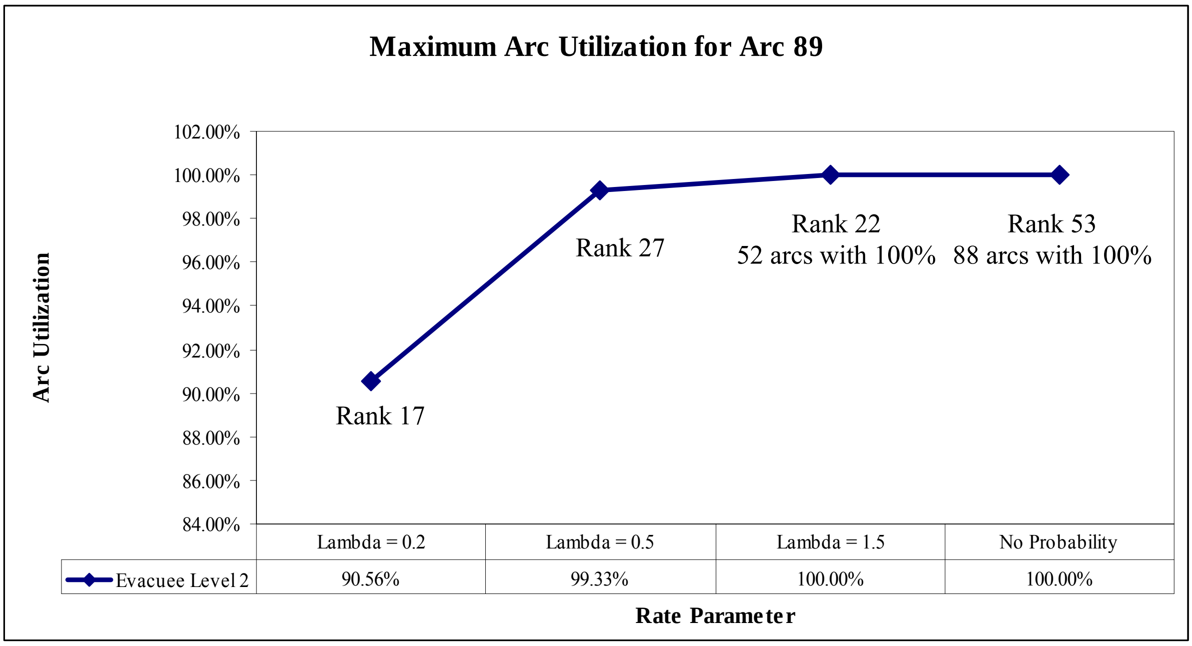


Figure 5.18. The maximum arc utilization for Arc 89 at Evacuee Demand Level 2.

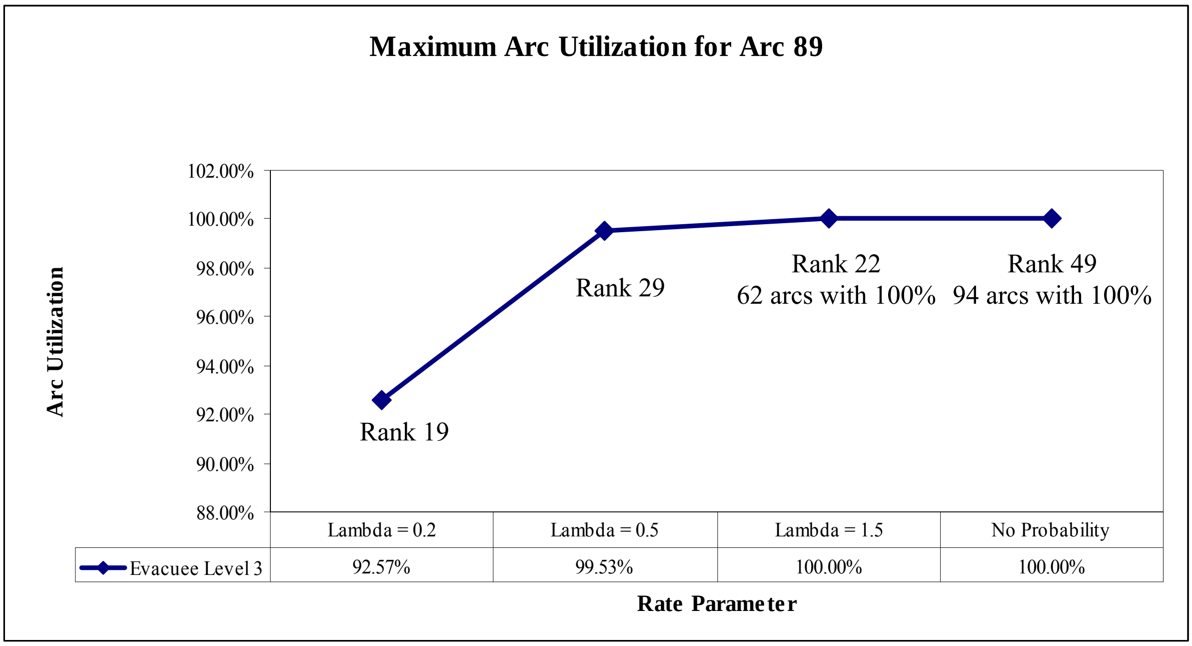


Figure 5.19. The maximum arc utilization for Arc 89 at Evacuee Demand Level 3.

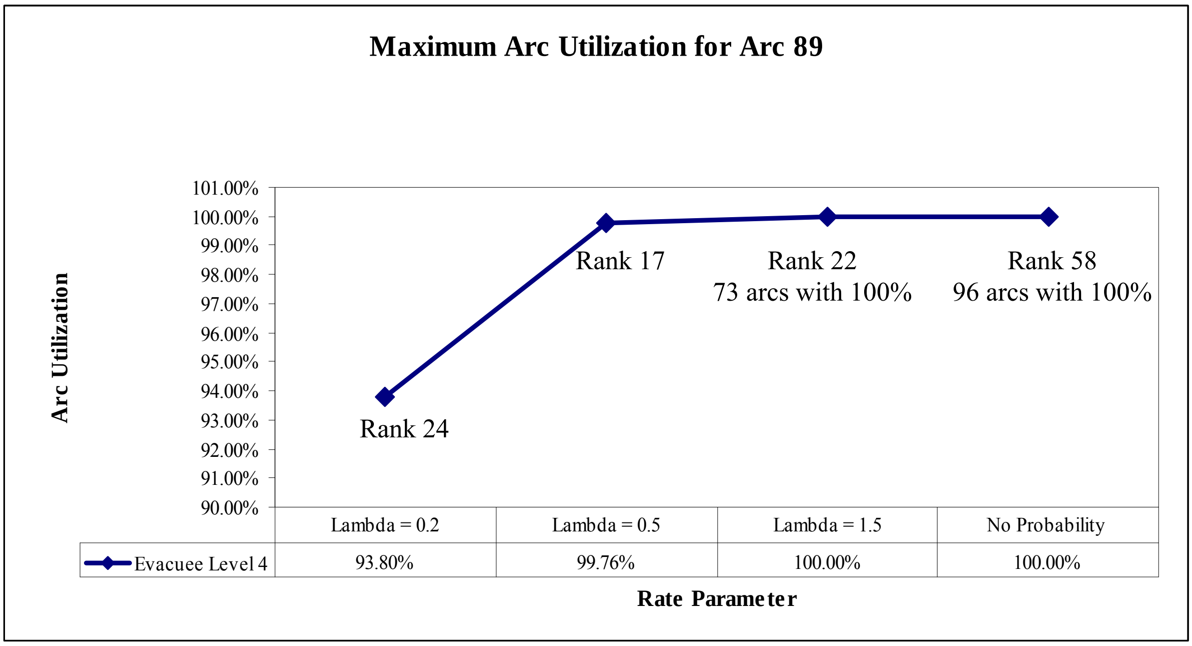


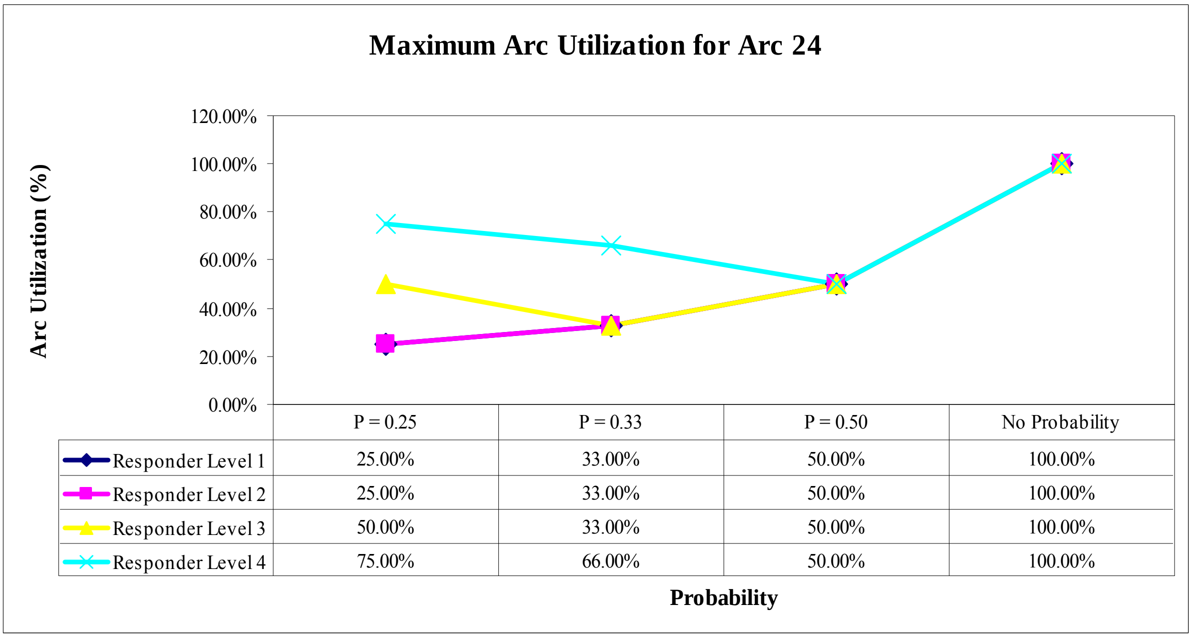
Figure 5.20. The maximum arc utilization for Arc 89 at Evacuee Demand Level 4.

5.6.2 Emergency Responder Flow – A Case Study

For the case of emergency responder flow, the arc utilization is used as the indicator of potential traffic congestion or traffic bottlenecking. Even though, in this case, the network density is quite low, the emergency management should still monitor the potential bottleneck. From the results of the emergency responder single-flow EERP model, the arc utilization changes by the different cases of the human response flow pattern. The emergency responder EERP model with no probability shows the highest arc utilization, followed by the emergency responder EERP model with probability P = 0.50, P = 0.25 and P = 0.33, respectively. Table 5.5. shows the ranking of the top 40 arcs in terms of maximum arc utilization for Responder Demand Level 4. This table shows that the maximum arc utilization changes according to the probability function P. Arc 24 (highlighted cell in Table 5.5) is used as an example to explain the impact of human response flow pattern of the emergency responders. This arc connects Node 7 to Node 18 and is highly utilized for Responder Demand Level 4. The maximum arc utilization decreases from 100% in the case of no probability to 50%, 66% and 75% for P = 0.50, 0.33 and 0.25, respectively. Figure 5.21 maximum arc utilization at Arc 24 at Responder Demand Levels 1 to 4. Figure 5.22 through Figure 5.25 also show the trends of maximum arc utilization in different demand levels along with the shifting of its ranking.

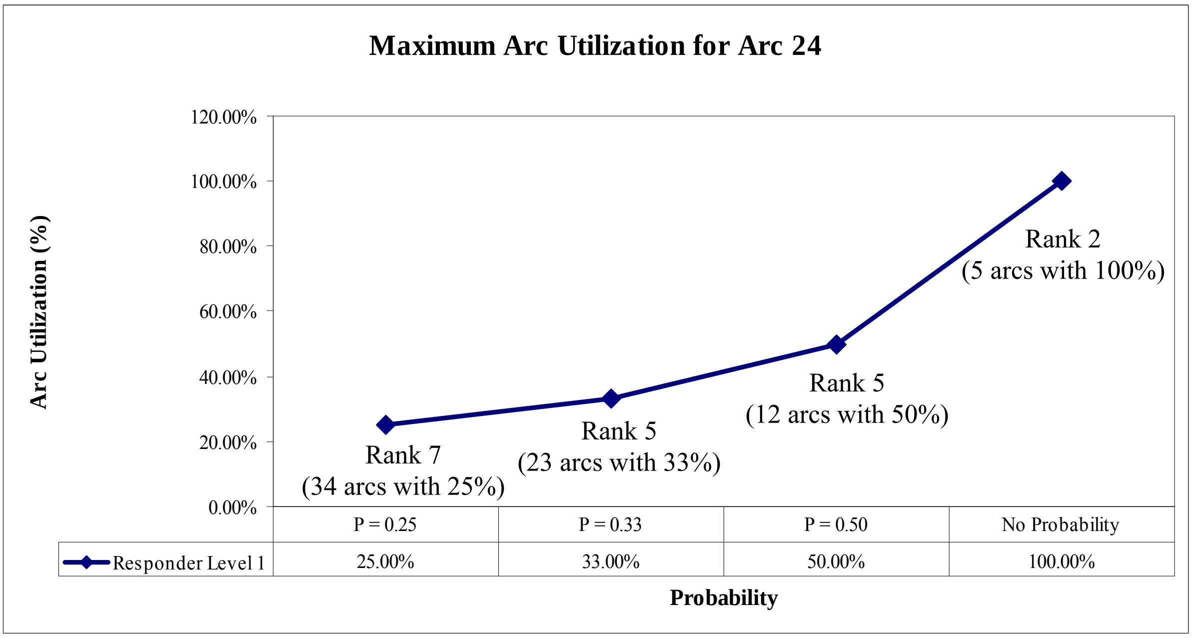
Table 5.5. The ranking of first 40 maximum arc utilization for the emergency responder single-flow EERP problem at Responder Demand Level 4.

	No Probability		$P = 0.25$		$P = 0.33$		$P = 0.50$	
Rank Position	Arc	Max Arc Util	Arc	Max Arc Util	Arc	Max Arc Util	Arc	Max Arc Util
1	2	100.00%	2	75.00%	2	66.00%	2	100.00%
2	4	100.00%	4	75.00%	6	66.00%	6	100.00%
3	6	100.00%	6	75.00%	12	66.00%	4	50.00%
4	10	100.00%	10	75.00%	14	66.00%	5	50.00%
5	14	100.00%	16	75.00%	16	66.00%	8	50.00%
6	16	100.00%	24	75.00%	24	66.00%	10	50.00%
7	20	100.00%	32	75.00%	32	66.00%	11	50.00%
8	24	100.00%	51	75.00%	34	66.00%	12	50.00%
9	25	100.00%	66	75.00%	51	66.00%	14	50.00%
10	28	100.00%	54	66.67%	54	66.00%	16	50.00%
11	30	100.00%	8	50.00%	64	66.00%	18	50.00%
12	32	100.00%	14	50.00%	66	66.00%	20	50.00%
13	34	100.00%	18	50.00%	82	66.00%	22	50.00%
14	36	100.00%	20	50.00%	101	66.00%	24	50.00%
15	46	100.00%	28	50.00%	104	66.00%	25	50.00%
16	51	100.00%	30	50.00%	107	66.00%	28	50.00%
17	54	100.00%	34	50.00%	110	66.00%	30	50.00%
18	56	100.00%	36	50.00%	120	66.00%	32	50.00%
19	60	100.00%	38	50.00%	123	66.00%	34	50.00%
20	62	100.00%	41	50.00%	130	66.00%	36	50.00%
21	64	100.00%	48	50.00%	4	55.00%	38	50.00%
22	66	100.00%	50	50.00%	57	49.50%	40	50.00%
23	70	100.00%	56	50.00%	10	44.00%	46	50.00%
24	72	100.00%	57	50.00%	8	43.40%	50	50.00%
25	73	100.00%	60	50.00%	80	39.60%	51	50.00%
26	76	100.00%	64	50.00%	9	36.00%	54	50.00%
27	78	100.00%	72	50.00%	3	33.00%	56	50.00%
28	80	100.00%	73	50.00%	5	33.00%	57	50.00%
29	82	100.00%	76	50.00%	18	33.00%	60	50.00%
30	87	100.00%	78	50.00%	20	33.00%	61	50.00%
31	88	100.00%	80	50.00%	22	33.00%	62	50.00%
32	90	100.00%	82	50.00%	25	33.00%	64	50.00%
33	92	100.00%	88	50.00%	26	33.00%	66	50.00%
34	96	100.00%	90	50.00%	28	33.00%	70	50.00%
35	100	100.00%	92	50.00%	30	33.00%	72	50.00%
36	101	100.00%	96	50.00%	36	33.00%	73	50.00%
37	104	100.00%	97	50.00%	38	33.00%	76	50.00%
38	106	100.00%	100	50.00%	40	33.00%	77	50.00%
39	107	100.00%	101	50.00%	46	33.00%	78	50.00%
40	110	100.00%	104	50.00%	50	33.00%	80	50.00%



	P = 0.25	P = 0.33	P = 0.50	No Probability
Responder Level 1	25.00%	33.00%	50.00%	100.00%
Responder Level 2	25.00%	33.00%	50.00%	100.00%
Responder Level 3	50.00%	33.00%	50.00%	100.00%
Responder Level 4	75.00%	66.00%	50.00%	100.00%

Figure 5.21. The maximum arc utilization for Arc 24 (connecting from Node 18 to Node 7).



	P = 0.25	P = 0.33	P = 0.50	No Probability
Responder Level 1	25.00%	33.00%	50.00%	100.00%

Figure 5.22. The maximum arc utilization for Arc 24 at Responder Demand Level 1.

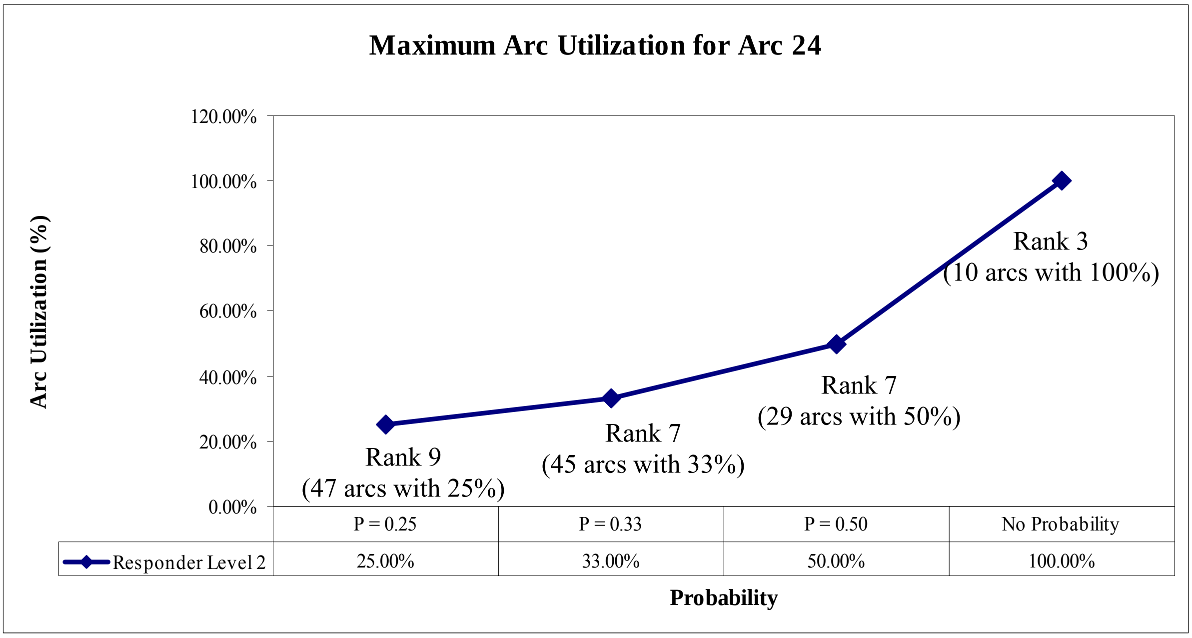


Figure 5.23. The maximum arc utilization for Arc 24 at Responder Demand Level 2.

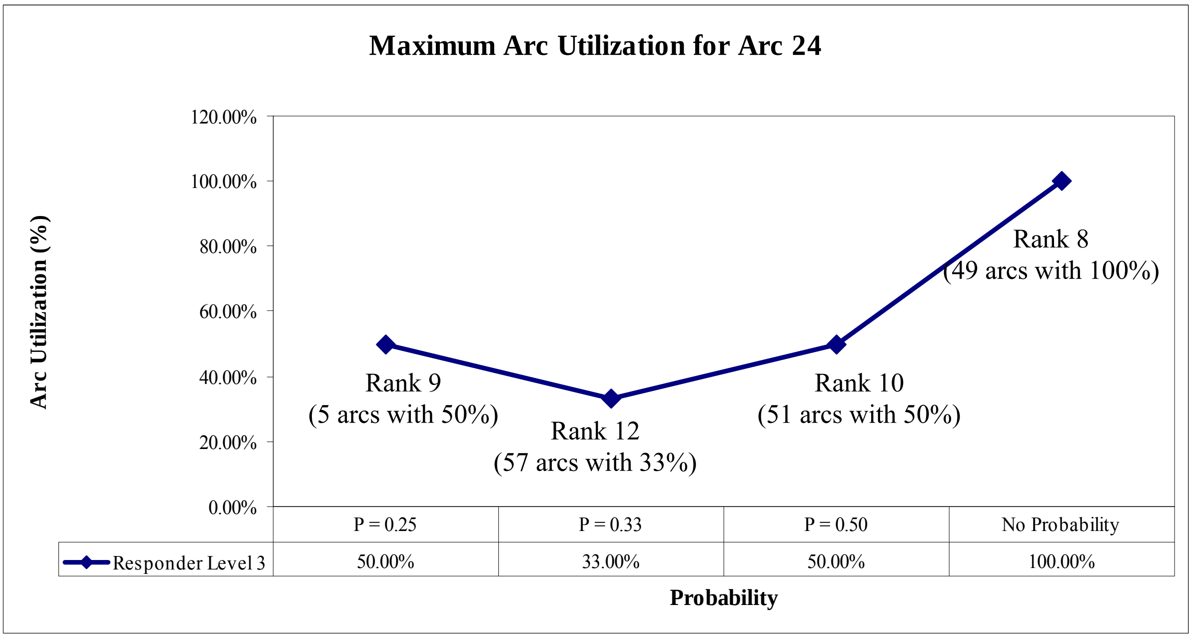


Figure 5.24. The maximum arc utilization for Arc 24 at Responder Demand Level 3.

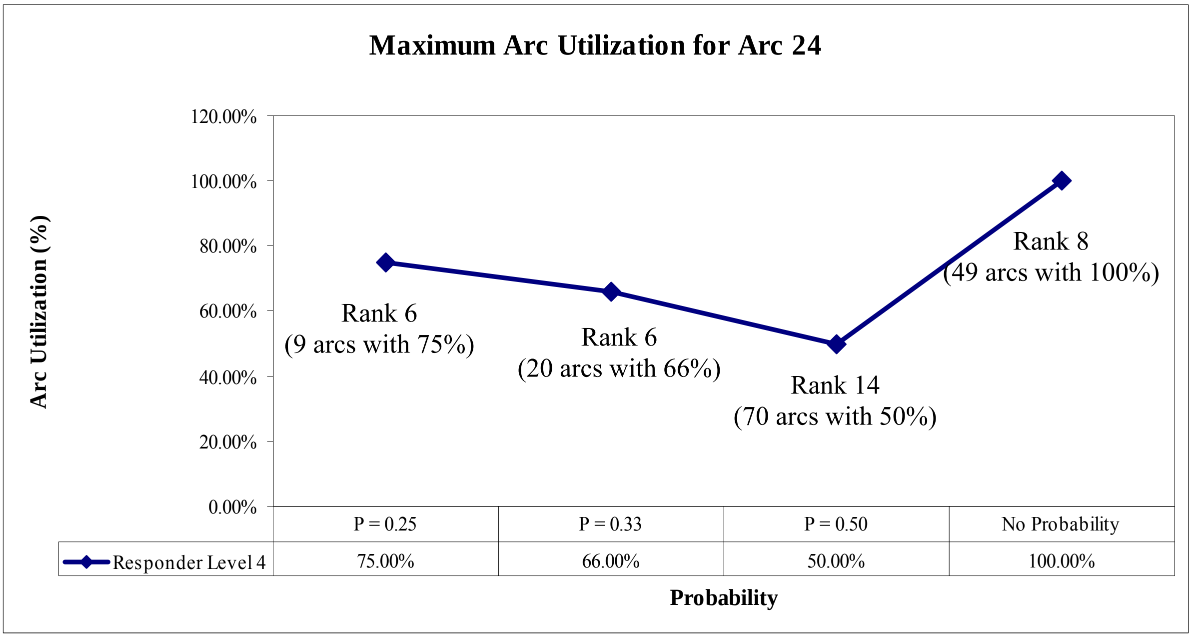


Figure 5.25. The maximum arc utilization for Arc 24 at Responder Demand Level 4.

5.7 Summary and Usefulness of Results

In this chapter, the study shows that network clearance time, potential traffic routing conflicts and arc utilizations are impacted by human response behavior. The exponential cumulative distribution function is used to represent the general human response behavior in the case of the emergency evacuee EERP problem, and a step function probability represents the flow movement pattern for emergency responders.

After integrating the general human response behavior into the EERP model, the network clearance time increases, which also impacts the number of potential routing conflicts. The EERP problems with the longer network clearance time for evacuees, such as the model with λ = 0.2, result in a higher number of routing conflicts since the evacuees reside in the network longer. For the emergency responder single-flow EERP problem, the probability P = 0.33 results in the longest network clearance time for the responders when compared to the problem with P = 0.25 and 0.50.

In the case of analyzing and identifying potential bottlenecks within the network during evacuations, the λ = 0.2 results in the smallest maximum arc utilization when compared to the emergency evacuee EERP problem with λ = 0.5 and 1.5, respectively. For the emergency responder EERP problem, the arc utilization probability also decreases as the P values decrease. This would suggest that, if the objective is to reduce the utilization of roadways by emergency responders, then a possible deployment strategy would be to use multiple but smaller waves of responders.

This study of the human response behavior and flow movement pattern will certainly be beneficial in the real-world. The emergency management can see the different results from the impact of human response behavior and flow movement patterns. For example, if the emergency event requires a mandatory evacuation, the emergency management can use the EERP model with the proper probability function (*i.e.*, λ = 1.5 in this research) to monitor the location with a high number of potential roadway conflicts and high arc utilization. Then, they can allocate their limited resources to the area where roadway conflicts and congestion are relatively high. It is important to note that the analysis in this chapter can be considered as a best case because variability is not considered.

CHAPTER 6:
SUMMARY OF RESEARCH AND PLANS FOR FUTURE WORK

6.1 Summary of the Research

This research studies of emergency evacuation route planning (EERP) problem in the case of unexpected hazard events, which give the emergency officials short or no notice to prepare and respond to the event. The focus here is incompatible and heterogeneous flow, more specifically emergency evacuee and emergency responders. Incompatible flow is defined as when the two different types of flow cannot occupy a given roadway segment, merge, or cross point at the same time. A significant contribution of this research is the incorporation of human response behavior within this problem and the impact of this behavior on the transportation network during an evacuation. In fact, the aspects of heterogeneous flow and human response behavior, or flow movement pattern, make this research different from previous studies.

CHAPTER 2 summarizes previous studies and shows different approaches for addressing the EERP problem. Generally, the previous studies can be divided into two categories: quantitative and qualitative approaches. The quantitative approaches for the EERP problem particularly focuses on one of two different perspectives – either moving the population out of the hazard area as quickly as possible or moving the emergency first responders into the hazard area. Qualitative approaches mainly consist of extracting information using interviews or survey instruments. These approaches are considered passive strategies.

In CHAPTER 3, two integer linear programming models are presented. The first model that presented is the single-flow model, which can be used for each emergency evacuee and emergency responder flow separately. In general, this model is considered the traditional model in the study of the EERP problem. The other EERP model is the two-flow model, which considers the two types of flow simultaneously. This model is the extension from the first one and adds the constraint to support the idea of heterogeneous and incompatible flows. The EERP problem is applied to a real-world dataset. The dataset is expanded in this study to include more demand levels for the emergency evacuees. In addition, emergency responder demand is arbitrarily selected and has four levels. Finally, the two models in CHAPTER 3 are solved to optimality. There clear and perhaps intuitive result that was verified is that the network clearance times for the evacuees and the responders depend on network utilization.

Next, in. CHAPTER 4 the issue of roadway routing conflicts is addressed. this research brings attention to the EERP problem in terms of traffic conflicts. An evacuation plan should consider not only transporting the population out of the hazard area as quickly as possible, but it should also consider the safety of the evacuees and the responders traversing the transportation network. By using the two-flow model presented in CHAPTER 3, the conflicts in the transportation network can be avoided by the incompatible flow constraint. The two-flow model in this chapter minimizes the routing conflicts to zero. However, the computational runtime for this analysis increases quite significantly.

In CHAPTER 5, the general human response behavior, or flow movement pattern, is considered. It is well-known that the general flow of evacuees can be represented by an S-shaped curve. The delayed decision during an emergency event creates slow movement at the beginning and then the flow moves faster until all evacuees move out of the hazard area. In this research, the human response behavior for emergency evacuee flow is represented by the exponential cumulative distribution function. This probability function is arbitrarily selected because of its shape. However, further study is needed to accurately characterize the movement pattern or probability function under different levels of evacuation orders. As expected, the results from the EERP model, along with the integration of the human response behavior, results in a longer network clearance time when compare to the EERP model that does not consider human response behavior. For the emergency responder case, the step function is used to represent the movement pattern. Similar to the evacuees, the step function causes delays and increases the network clearance time for the emergency responders.

Next, the issue of traffic congestion or traffic bottlenecking, is considered. Arc utilization is used as performance measure for finding potential traffic bottlenecks. From the analysis, arc utilizations change when the human response behavior is applied. Two parameters From the experiments of emergency evacuees, the $\lambda = 0.2$ gives the most impact to the arc utilization and generates the smallest amount of arc utilization when compare to $\lambda =$ 0.5 and 1.5, respectively. On the other hand, the probability of 0.25 gives the smallest arc utilization followed by the probability of 0.33 and 0.50 in the case of emergency responders. As a result, the traffic bottleneck tends to shift depending upon the level of evacuation order that is issued.

The integration of human response behavior and flow movement patterns enhances the EERP model and provides more useful information to the emergency officials to help them decide when and how to allocate their limited resources within the transportation network. For instance, the emergency officials can make the evacuation order decision based on the general human response behavior. Furthermore, the officials can mobilize the emergency ground units much more effectively to the areas with high potential to be traffic flow constraints. Additionally, the results show the allocation of the traffic flow in order to eliminate traffic roadway conflicts. Again, the results in this research are considered to be the best case because there is no variability such as stochastic roadway travel times, availability of roadways due to unpredicted closures, *etc*.

6.2 Plans for Future Work

It is felt that there are several fruitful areas of research that could be pursued based on the results of this research investigation. First, interesting application that will strengthen the traffic models is the consideration of contraflow lane reversals. Contraflow lane reversals is "…the reversal of traffic flow in one or more of inbound lanes (or shoulders) for use in the outbound direction with the goal of increasing capacity" (FHWA 2003). With this application, we believe that the network clearance time can be decreased because of the increasing arc capacity. Lim and Wolshon (2005) and Saleh (2008) are examples of studies that consider contraflow lane reversals in emergency situations. Contraflow lane reversals do not necessarily guarantee doubled roadway capacity. Furthermore, evacuee and responder safety in the form of roadway incidents is a concern when using contraflow in the real-world emergency situations, especially under the human response behavior.

Second, the effect of queuing should be included in the EERP model. In this study, we assume the travel time between merge and cross points is independent from the amount of flow on the roadway. The application of queuing will make the model much more accurate in that it will consider flow-dependent times.

Finally, the integration of a Geographic Information System (GIS) framework with the EERP model is a possibility for further study. In previous studies, the research models use numerical examples instead of real-world datasets. Sometimes, real datasets are used, is in this research, but they do not represent a real-world situation in real-time. By using the GIS data, the emergency evacuation route planning model can be applied to any location that can be characterized by the data.

APPENDIX A:
SUMMARY OF THE MONTICELLO, MINNESOTA DATASET

Arc Number	From Node	To Node	Arc Capacity	Travel Time
1	1	2	150	0
2	2	1	150	0
3	2	3	150	18
4	3	2	150	18
5	2	4	150	9
6	4	2	150	9
7	3	5	250	6
8	5	3	250	6
9	3	6	150	5
10	6	3	150	5
11	4	5	100	17
12	5	4	100	17
13	4	7	150	10
14	7	4	150	10
15	4	10	100	15
16	10	4	100	15
17	5	16	250	11
18	16	5	250	11
19	6	9	200	9
20	9	6	200	9
21	7	10	150	8
22	10	7	150	8
23	7	18	100	7
24	18	7	100	7
25	8	9	150	17
26	9	8	150	17
27	8	12	150	6
28	12	8	150	6
29	9	11	200	2
30	11	9	200	2
31	10	16	150	5
32	16	10	150	5
33	10	17	100	3
34	17	10	100	3
35	11	13	100	3
36	13	11	100	3
37	11	14	200	4
38	14	11	200	4
39	12	24	150	15
40	24	12	150	15

Arc Number	From Node	To Node	Arc Capacity	Travel Time
41	12	41	100	9
42	41	12	100	9
43	13	14	100	8
44	14	13	100	8
45	13	19	100	6
46	19	13	100	6
47	13	41	100	8
48	41	13	100	8
49	14	20	200	5
50	20	14	200	5
51	15	16	150	1
52	16	15	150	1
53	15	20	150	4
54	20	15	150	4
55	15	21	100	9
56	21	15	100	9
57	16	17	100	5
58	17	16	100	5
59	16	22	250	9
60	22	16	250	9
61	17	18	100	8
62	18	17	100	8
63	17	22	100	12
64	22	17	100	12
65	18	23	100	11
66	23	18	100	11
67	19	20	100	11
68	20	19	100	11
69	19	25	100	12
70	25	19	100	12
71	20	26	200	12
72	26	20	200	12
73	21	22	100	5
74	22	21	100	5
75	21	27	100	8
76	27	21	100	8
77	22	23	100	3
78	23	22	100	3
79	22	47	250	9
80	47	22	250	9
81	23	47	150	5
82	47	23	150	5
83	24	25	200	11
84	25	24	200	11
85	25	26	200	13

Arc Number	From Node	To Node	Arc Capacity	Travel Time
86	26	25	200	13
87	26	27	150	1
88	27	26	150	1
89	26	39	200	13
90	39	26	200	13
91	27	28	150	2
92	28	27	150	2
93	28	29	150	5
94	29	28	150	5
95	28	32	100	4
96	32	28	100	4
97	29	30	150	1
98	30	29	150	1
99	29	46	100	2
100	46	29	100	2
101	29	47	100	4
102	47	29	100	4
103	30	31	200	3
104	31	30	200	3
105	30	34	250	7
106	34	30	250	7
107	30	47	250	3
108	47	30	250	3
109	31	33	100	3
110	33	31	100	3
111	32	40	100	11
112	40	32	100	11
113	32	46	100	3
114	46	32	100	3
115	33	35	100	5
116	35	33	100	5
117	33	46	100	4
118	46	33	100	4
119	34	36	100	2
120	36	34	100	2
121	34	37	250	2
122	36	34	250	2
123	34	36	100	2
124	37	35	100	2
125	35	40	100	10
126	36	35	100	10
127	35	48	100	3
128	48	35	100	3
129	36	48	100	3
130	48	36	100	3

Arc Number	From Node	To Node	Arc Capacity	Travel Time
131	37	38	250	1
132	38	37	250	1
133	37	44	100	5
134	44	37	100	5
135	38	45	250	3
136	45	38	250	3
137	39	40	200	1
138	40	39	200	1
139	40	42	200	6
140	42	40	200	6
141	48	42	100	2
142	42	48	100	2
143	48	43	100	3
144	43	48	100	3
145	42	43	200	2
146	43	42	200	2
147	43	44	200	1
148	44	43	200	1
149	44	45	200	1
150	45	44	200	1
151	48	49	52439	0
152	49	48	52439	0

APPENDIX B:
RESULTS OF THE TWO-FLOW EERP MODEL FOR EVACUEES AND EMERGENCY RESPONDERS SUMMARIZING ROUTING CONFLICTS UNDER INDEPENDENT OPTIMIZATION FOR

Evacuee demand at 27,902 vehicles vs. Emergency responder at 1,316 vehicles (U = 39%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	20	2.57	2.28
$\lambda = 0.20$ vs. $P = 0.25$	20	2.57	2.30
$\lambda = 0.20$ vs. $P = 0.50$	17	2.57	2.30
$\lambda = 0.50$ vs. $P = 0.33$	14	2.62	2.28
$\lambda = 0.50$ vs. $P = 0.25$	11	2.62	2.30
$\lambda = 0.50$ vs. $P = 0.50$	10	2.62	2.30
$\lambda = 1.50$ vs. $P = 0.33$	7	2.55	2.28
$\lambda = 1.50$ vs. $P = 0.25$	6	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.50$	6	2.55	2.30

Evacuee demand at 27,902 vehicles vs. Emergency responder at 2,618 vehicles (U = 41%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	33	2.57	2.28
$\lambda = 0.20$ vs. $P = 0.25$	36	2.57	2.32
$\lambda = 0.20$ vs. $P = 0.50$	21	2.57	2.33
$\lambda = 0.50$ vs. $P = 0.33$	20	2.62	2.28
$\lambda = 0.50$ vs. $P = 0.25$	22	2.62	2.32
$\lambda = 0.50$ vs. $P = 0.50$	12	2.62	2.33
$\lambda = 1.50$ vs. $P = 0.33$	10	2.55	2.28
$\lambda = 1.50$ vs. $P = 0.25$	9	2.55	2.32
$\lambda = 1.50$ vs. $P = 0.50$	7	2.55	2.33

Evacuee demand at 27,902 vehicles vs. Emergency responder at 5,230 vehicles (U = 44%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	42	2.57	2.30
$\lambda = 0.20$ vs. $P = 0.25$	58	2.57	2.33
$\lambda = 0.20$ vs. $P = 0.50$	24	2.57	2.35
$\lambda = 0.50$ vs. $P = 0.33$	25	2.62	2.30
$\lambda = 0.50$ vs. $P = 0.25$	28	2.62	2.33
$\lambda = 0.50$ vs. $P = 0.50$	21	2.62	2.35
$\lambda = 1.50$ vs. $P = 0.33$	16	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.25$	16	2.55	2.33
$\lambda = 1.50$ vs. $P = 0.50$	13	2.55	2.35

Evacuee demand at 27,902 vehicles vs. Emergency responder at 10,460 vehicles (*U* =51%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	91	2.57	2.42
$\lambda = 0.20$ vs. $P = 0.25$	77	2.57	2.38
$\lambda = 0.20$ vs. $P = 0.50$	52	2.57	2.35
$\lambda = 0.50$ vs. $P = 0.33$	74	2.62	2.42
$\lambda = 0.50$ vs. $P = 0.25$	60	2.62	2.38
$\lambda = 0.50$ vs. $P = 0.50$	49	2.62	2.35
$\lambda = 1.50$ vs. $P = 0.33$	53	2.55	2.42
$\lambda = 1.50$ vs. $P = 0.25$	43	2.55	2.38
$\lambda = 1.50$ vs. $P = 0.50$	37	2.55	2.35

Evacuee demand at 33,832 vehicles vs. Emergency responder at 1,316 vehicles (*U* = 47%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	28	2.60	2.28
$\lambda = 0.20$ vs. $P = 0.25$	32	2.60	2.30
$\lambda = 0.20$ vs. $P = 0.50$	26	2.60	2.30
$\lambda = 0.50$ vs. $P = 0.33$	17	2.55	2.28
$\lambda = 0.50$ vs. $P = 0.25$	18	2.55	2.30
$\lambda = 0.50$ vs. $P = 0.50$	15	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.33$	9	2.55	2.28
$\lambda = 1.50$ vs. $P = 0.25$	5	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.50$	5	2.55	2.30

Evacuee demand at 33,832 vehicles vs. Emergency responder at 2,618 vehicles (*U* = 49%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	47	2.60	2.28
$\lambda = 0.20$ vs. $P = 0.25$	57	2.60	2.32
$\lambda = 0.20$ vs. $P = 0.50$	30	2.60	2.33
$\lambda = 0.50$ vs. $P = 0.33$	26	2.55	2.28
$\lambda = 0.50$ vs. $P = 0.25$	26	2.55	2.32
$\lambda = 0.50$ vs. $P = 0.50$	17	2.55	2.33
$\lambda = 1.50$ vs. $P = 0.33$	10	2.55	2.28
$\lambda = 1.50$ vs. $P = 0.25$	8	2.55	2.32
$\lambda = 1.50$ vs. $P = 0.50$	5	2.55	2.33

Evacuee Demand at 33,832 vehicles vs. Emergency Responder Demand at 5,230 vehicles (*U* = 52%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	55	2.60	2.30
$\lambda = 0.20$ vs. $P = 0.25$	72	2.60	2.33
$\lambda = 0.20$ vs. $P = 0.50$	40	2.60	2.35
$\lambda = 0.50$ vs. $P = 0.33$	35	2.55	2.30
$\lambda = 0.50$ vs. $P = 0.25$	38	2.55	2.33
$\lambda = 0.50$ vs. $P = 0.50$	22	2.55	2.35
$\lambda = 1.50$ vs. $P = 0.33$	19	2.55	2.30
$\lambda = 1.50$ vs. $P = 0.25$	18	2.55	2.33
$\lambda = 1.50$ vs. $P = 0.50$	17	2.55	2.35

Evacuee Demand at 33,832 vehicles vs. Emergency Responder Demand at 10,460 vehicles (*U* =59%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	114	2.60	2.42
$\lambda = 0.20$ vs. $P = 0.25$	110	2.60	2.38
$\lambda = 0.20$ vs. $P = 0.50$	76	2.60	2.35
$\lambda = 0.50$ vs. $P = 0.33$	89	2.55	2.42
$\lambda = 0.50$ vs. $P = 0.25$	68	2.55	2.38
$\lambda = 0.50$ vs. $P = 0.50$	54	2.55	2.35
$\lambda = 1.50$ vs. $P = 0.33$	100	2.55	2.42
$\lambda = 1.50$ vs. $P = 0.25$	75	2.55	2.38
$\lambda = 1.50$ vs. $P = 0.50$	80	2.55	2.35

Evacuee Demand at 38,051 vehicles vs. Emergency Responder Demand at 1,316 vehicles (*U* = 53%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	20	2.67	2.28
$\lambda = 0.20$ vs. $P = 0.25$	22	2.67	2.30
$\lambda = 0.20$ vs. $P = 0.50$	18	2.67	2.30
$\lambda = 0.50$ vs. $P = 0.33$	17	2.65	2.28
$\lambda = 0.50$ vs. $P = 0.25$	18	2.65	2.30
$\lambda = 0.50$ vs. $P = 0.50$	15	2.65	2.30
$\lambda = 1.50$ vs. $P = 0.33$	8	2.68	2.28
$\lambda = 1.50$ vs. $P = 0.25$	6	2.68	2.30
$\lambda = 1.50$ vs. $P = 0.50$	6	2.68	2.30

Evacuee Demand at 38,051 vehicles vs. Emergency Responder Demand at 2,618 vehicles (U = 54%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	42	2.67	2.28
$\lambda = 0.20$ vs. $P = 0.25$	46	2.67	2.32
$\lambda = 0.20$ vs. $P = 0.50$	22	2.67	2.33
$\lambda = 0.50$ vs. $P = 0.33$	27	2.65	2.28
$\lambda = 0.50$ vs. $P = 0.25$	29	2.65	2.32
$\lambda = 0.50$ vs. $P = 0.50$	15	2.65	2.33
$\lambda = 1.50$ vs. $P = 0.33$	12	2.68	2.28
$\lambda = 1.50$ vs. $P = 0.25$	11	2.68	2.32
$\lambda = 1.50$ vs. $P = 0.50$	7	2.68	2.33

Evacuee Demand at 38,051 vehicles vs. Emergency Responder Demand at 5,230 vehicles (U = 58%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	62	2.67	2.30
$\lambda = 0.20$ vs. $P = 0.25$	67	2.67	2.33
$\lambda = 0.20$ vs. $P = 0.50$	29	2.67	2.35
$\lambda = 0.50$ vs. $P = 0.33$	35	2.65	2.30
$\lambda = 0.50$ vs. $P = 0.25$	46	2.65	2.33
$\lambda = 0.50$ vs. $P = 0.50$	24	2.65	2.35
$\lambda = 1.50$ vs. $P = 0.33$	22	2.68	2.30
$\lambda = 1.50$ vs. $P = 0.25$	21	2.68	2.33
$\lambda = 1.50$ vs. $P = 0.50$	13	2.68	2.35

Evacuee Demand at 38,051 vehicles vs. Emergency Responder Demand at 10,460 vehicles (U =65%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	110	2.67	2.42
$\lambda = 0.20$ vs. $P = 0.25$	85	2.67	2.38
$\lambda = 0.20$ vs. $P = 0.50$	62	2.67	2.35
$\lambda = 0.50$ vs. $P = 0.33$	85	2.65	2.42
$\lambda = 0.50$ vs. $P = 0.25$	63	2.65	2.38
$\lambda = 0.50$ vs. $P = 0.50$	62	2.65	2.35
$\lambda = 1.50$ vs. $P = 0.33$	67	2.68	2.42
$\lambda = 1.50$ vs. $P = 0.25$	62	2.68	2.38
$\lambda = 1.50$ vs. $P = 0.50$	47	2.68	2.35

Evacuee Demand at 41,950 vehicles vs. Emergency Responder Demand at 1,316 vehicles (*U* = 58%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	39	2.63	2.28
$\lambda = 0.20$ vs. $P = 0.25$	40	2.63	2.30
$\lambda = 0.20$ vs. $P = 0.50$	47	2.63	2.30
$\lambda = 0.50$ vs. $P = 0.33$	18	2.75	2.28
$\lambda = 0.50$ vs. $P = 0.25$	21	2.75	2.30
$\lambda = 0.50$ vs. $P = 0.50$	17	2.75	2.30
$\lambda = 1.50$ vs. $P = 0.33$	11	2.63	2.28
$\lambda = 1.50$ vs. $P = 0.25$	11	2.63	2.30
$\lambda = 1.50$ vs. $P = 0.50$	10	2.63	2.30

Evacuee Demand at 41,950 vehicles vs. Emergency Responder Demand at 2,618 vehicles (*U* = 59%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	59	2.63	2.28
$\lambda = 0.20$ vs. $P = 0.25$	65	2.63	2.32
$\lambda = 0.20$ vs. $P = 0.50$	40	2.63	2.33
$\lambda = 0.50$ vs. $P = 0.33$	29	2.75	2.28
$\lambda = 0.50$ vs. $P = 0.25$	34	2.75	2.32
$\lambda = 0.50$ vs. $P = 0.50$	19	2.75	2.33
$\lambda = 1.50$ vs. $P = 0.33$	14	2.63	2.28
$\lambda = 1.50$ vs. $P = 0.25$	19	2.63	2.32
$\lambda = 1.50$ vs. $P = 0.50$	10	2.63	2.33

Evacuee Demand at 41,950 vehicles vs. Emergency Responder Demand at 5,230 vehicles (*U* = 63%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
$\lambda = 0.20$ vs. $P = 0.33$	83	2.63	2.30
$\lambda = 0.20$ vs. $P = 0.25$	102	2.63	2.33
$\lambda = 0.20$ vs. $P = 0.50$	51	2.63	2.35
$\lambda = 0.50$ vs. $P = 0.33$	40	2.75	2.30
$\lambda = 0.50$ vs. $P = 0.25$	42	2.75	2.33
$\lambda = 0.50$ vs. $P = 0.50$	25	2.75	2.35
$\lambda = 1.50$ vs. $P = 0.33$	25	2.63	2.30
$\lambda = 1.50$ vs. $P = 0.25$	24	2.63	2.33
$\lambda = 1.50$ vs. $P = 0.50$	16	2.63	2.35

Evacuee Demand at 41,950 vehicles vs. Emergency Responder Demand at 10,460 vehicles (U =70%)			
Human Response Flow Pattern	**Routing Conflicts**	**Solution Time (Minutes)**	
		Evacuee Only	Responder Only
λ = 0.20 vs. P = 0.33	140	2.63	2.42
λ = 0.20 vs. P = 0.25	119	2.63	2.38
λ = 0.20 vs. P = 0.50	93	2.63	2.35
λ = 0.50 vs. P = 0.33	82	2.75	2.42
λ = 0.50 vs. P = 0.25	56	2.75	2.38
λ = 0.50 vs. P = 0.50	56	2.75	2.35
λ = 1.50 vs. P = 0.33	69	2.63	2.42
λ = 1.50 vs. P = 0.25	59	2.63	2.38
λ = 1.50 vs. P = 0.50	58	2.63	2.35

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