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Modeling Lane-based Traffic Flow In Emergency Situations In The Presence Of Multiple Heterogeneous Flows

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MODELING LANE-BASED TRAFFIC FLOW IN EMERGENCY SITUATIONS IN THE PRESENCE OF MULTIPLE HETEROGENEOUS FLOWS

by

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ABSTRACT

In recent years, natural, man-made and technological disasters have been increasing in magnitude and frequency of occurrence. Terrorist attacks have increased after the September 11, 2001. Some authorities suggest that global warming is partly the blame for the increase in frequency of natural disasters, such as the series of hurricanes in the early-2000's. Furthermore, there has been noticeable growth in population within many metropolitan areas not only in the US but also worldwide. 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.

This research considers aspects of evacuation routing never before considered 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 unanticipated emergencies. By incompatible, it is meant that the two different flows cannot occupy a given lane and merge or crossing point in the travel network at the same time. In addition, in large-scale evacuations, travel lane normal flow directions can be reversed dynamically to their contraflow directions depending upon the degree of the emergency. These characteristics provide the basis for this investigation. This research considers the multiple flow EERP problem where the network travel lanes can be reconfigured using contraflow lane reversals. The first flow is vehicular flow of evacuees from the source of a hazard to destinations of safety, and the second flow is the emergency first responders to the hazard source.

After presenting a review of the work related to the multiple flow EERP problem, mathematical formulations are proposed for three variations of the EERP problem where the objective for each problem is to identify an evacuation plan (*i.e.*, a flow schedule and network contraflow lane configuration) that minimizes network clearance time. Before the proposed formulations, the evacuation problem that considers only the flow of evacuees out of the network, which is viewed as a maximum flow problem, is formulated as an integer linear program. Then, the first proposed model formulation, which addresses the problem that considers the flow of evacuees under contraflow conditions, is presented. Next, the proposed formulation is expanded to consider the flow of evacuees and responders through the network but under normal flow conditions. Lastly, the two-flow problem of evacuees and responders under contraflow conditions is formulated. Using real-world population and travel network data, the EERP problems are each solved to optimality; however, the time required to solve the problems increases exponentially as the problem grows in size and complexity. Due to the intractable nature of the problems as the size of the network increases, a genetic-based heuristic solution procedure that generates evacuation network configurations of reasonable quality is proposed. The proposed heuristic solution approach generates evacuation plans in the order of minutes, which is desirable in emergency situations and needed to allow for immediate evacuation routing plan dissemination and implementation in the targeted areas.

To my husband, my angel daughter Tuline and my grandmother Merriam (peace be upon her)

ACKNOWLEDGMENTS

Though only my name appears on the cover of this dissertation, there is great number of people who helped make this dissertation possible. I would like to express my deepest gratitude to all of those people who provided me with support, advise, love and encouragement.

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I would like to thank my siblings and sisters-in-law for their sincerity. Especially, I would like to thank my sister Merriam for being there for me, and for always finding the right words to soothe me, and for always believing in me. Also, I would like to express gratitude to my dear friends Wafa and Ali for their support, encouragement, and joyful times I had with them after long hours of work.

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CHAPTER 1: INTRODUCTION

1.1 Overview

Over the last 15 years, there has been an ever-increasing need for effective tools for prevention of, preparedness for and response to disasters. These disasters, which can be classified into three primary categories, are shown in Figure 1.1. The figure shows the main categories of disaster (or hazard) events and lists several examples of these events for each category. Effective disaster management presents a number of challenges to the responsible agencies on the local, regional and federal levels. Most recently, the United States Department of Homeland Security (USDHS) developed the National Response Plan (NRP). The NRP is a document that defines disaster/hazard management activities at the highest level in order to help disambiguate roles and responsibilities on the lower levels during the time of an emergency (USDHS, 2004).

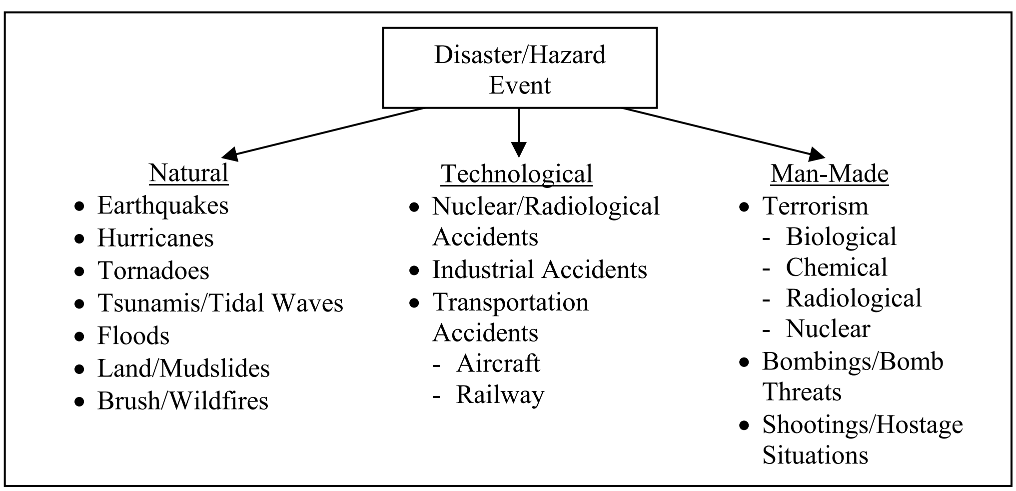


Figure 1.1. Taxonomy of disasters/hazards (FEMA, 2006).

In recent years, natural, man-made and technological disasters have increased in frequency and in magnitude of occurrence. Specifically, technological and man-made disaster risk has increased due in large part to the evolving and growing threat of terrorist attacks against the US (Muller, 2005). Natural disaster risk has increased due to progressively changing weather patterns caused partly by global warming (FEMA, 2006). The Federal Emergency Management Agency (FEMA) reports that since 1953, 1,536 disasters have occurred in the US (USDHS, 2004). Table 1.1 shows a sampling of the lives lost and property damage caused by several different types of disasters just over the last five years (BBC, 2001; Bernardino, 2003; CNN, 2003; CTV, 2006; Peiris, 2005; TenBruggencate and Daysog, 2006; UN, 2005).

Table 1.1. Disaster/Hazard events over the last five years.

Name of Event	**Location**	**Lives Lost**	**Property Damage**	**Date**
Tsunami	South and Southeast Asia	230,000 +	$10 billion +	12/26/04
Floods	Phetchabun, Thailand	170	$5 million +	08/01
09/11/2001 (Terrorist Attack)	NY, PA, Wash DC, USA	2,986	$112.5 billion	09/11/01
Cedar Wildfires	La Verne, CA, USA	14	$1 billion +	10/03
Mudslides	San Bernardino Mountains, CA, USA	7	$1 million +	12/03
Shadikor (Dam)	Pasni, Quetta, Pakistan	1000+	$15 million +	02/05
Hurricane Katrina	Louisiana, Mississippi, Alabama, USA	1,604	$75 billion	08/29/05
Hurricane Rita	Texas, Louisiana, USA	119	$10 billion	09/24/05
Borger Wildfires	Texas, USA	11	$10 million +	03/06
Kaloko Reservoir (Dam)	Kauai. HI, USA	1-7	$14.5 million	03/15/06

Towards the end of 2004, Asia faced the most powerful earthquake in 40 years, which erupted under the Indian Ocean near Sumatra. It caused giant, deadly waves that crashed ashore in nearly a dozen countries, resulting in over 230,000 persons dead and approximately 128,329 persons missing. Also, in 2005, the US Gulf Coast states suffered greatly from the intensity of Hurricane Katrina. The storm surge from Katrina caused catastrophic damage along the coastlines of Louisiana, Mississippi and Alabama. Eighty percent of the city of New Orleans was devastated by Katrina. Wind damage was reported well inland, impeding relief efforts. Katrina is estimated to be responsible for $75 billion in damage, making it the costliest hurricane in US history. The storm killed 1,604 people, becoming the deadliest US hurricane since the 1982 Okeechobee Hurricane (NPR, 2005).

Moreover, the population surge into the coastal areas in the US has been tremendous in the recent decades. Due to this population increase, the importance of a well-planned and well-organized evacuation is much greater than before. The population along the Gulf Coast counties has increased to approximately 45 million in recent years (Hobbs, 2002; Urbina and Wolshon, 2003). In addition, during weekends and holidays, the population of the coastal regions increases from 10 to 100 percent. Due to diverse population pockets along the coast and infrastructure needs that have not kept pace with the rapid local growth, emergency evacuation complications and delays could lead to catastrophic results. This is especially true in the larger cities such as Houston, TX, New Orleans, LA, Miami, FL and Tampa, FL. Figure 1.2 and Figure 1.3 show the population density in 1900 and 2000, respectively. One can conclude that several Gulf Coast states in the US have experienced significant increases in population, such as Texas and Florida.

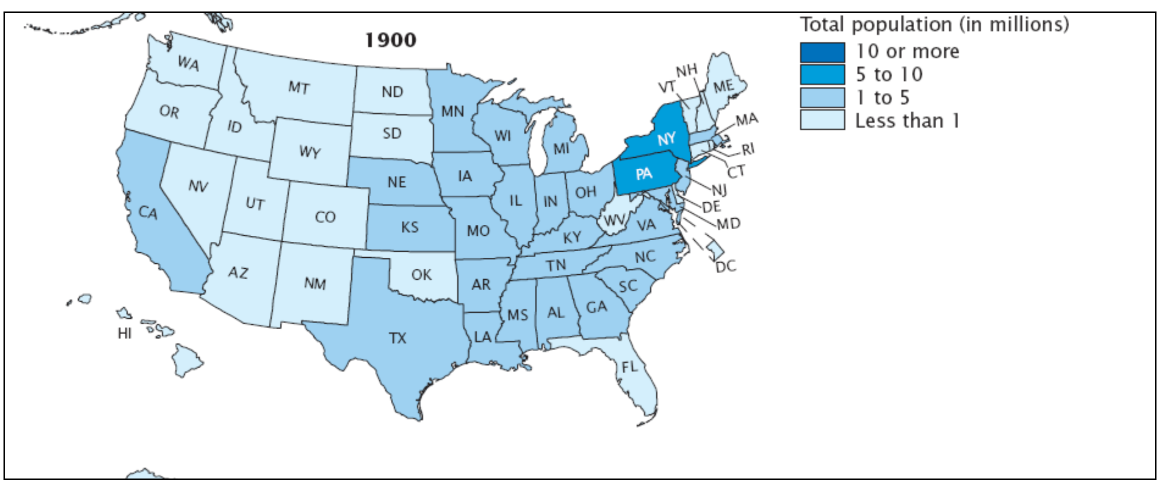


Figure 1.2. Population density of US in 1990 (obtained from Hobbs (2002)).

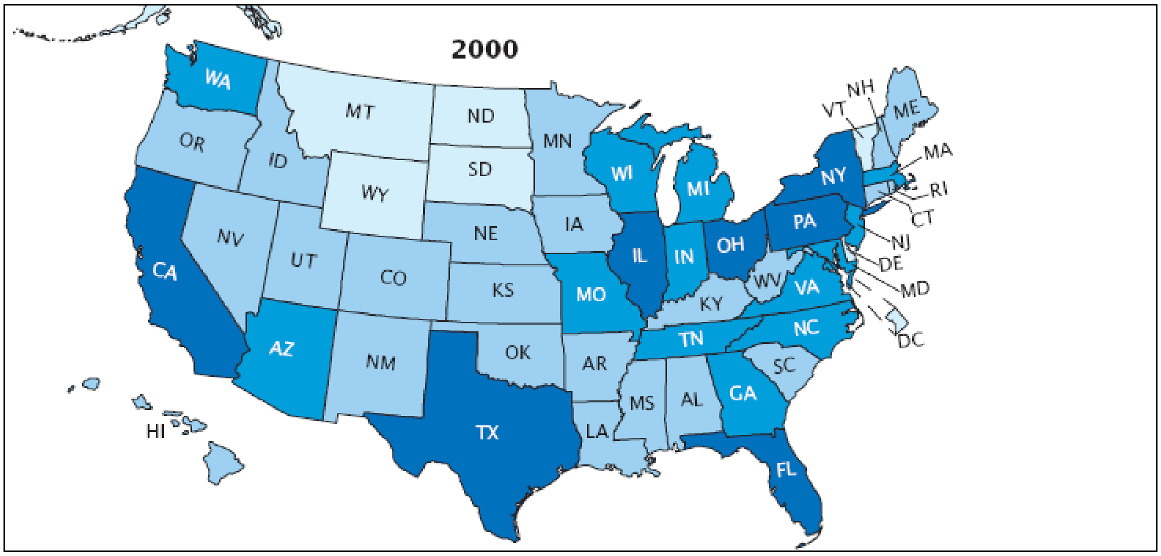


Figure 1.3. Population density of US in 2000 (obtained from Hobbs (2002)).

1.2 Disaster Management

In general, there are five phases of disaster management. These include prevention, preparedness, response, recovery and mitigation (Jain and McLean, 2006). The decision-making tools differ based on the disaster management phase for which they are designed. Disaster prevention involves analyzing vulnerabilities, monitoring and detecting conditions of disaster events. The preparedness phase primarily involves planning, which includes determining the impact (or magnitude) of a disaster event. This phase also includes training of appropriate response personnel for handling the emergency events and the testing of emergency response systems. Response includes evaluating the impact of a disaster event using real-time updates and using the available information to project the current and future impact of the disaster. It also includes tools for executing and evaluating response actions and strategies based on the current and projected impact of the disaster event. The recovery phase evaluates the long-term impact of a disaster and response actions. During this phase, tools can be used for evaluating alternative recovery actions and strategies based on the current and projected impact. Finally, mitigation focuses on post-disaster activities. Applications for mitigation may overlap in function and scope with other phases since mitigation measures may be implemented prior to, during, or even after an incident (USDHS, 2004). In this research investigation, the focus is primarily on the response phase of disaster management.

1.3 The Expectation of Emergency Disasters and Events

The categories of disaster and hazard events given by FEMA and shown in Figure 1.1 can be further categorized by their expectation – expected or unexpected (see Figure 1.4). Emergency response during unexpected events is slightly different than that during events that are expected, or anticipated. 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 impacted areas. In addition, emergency management officials have some *a priori* knowledge about the type of event, the trajectory of the event and the degree of impact to the areas. Unexpected (or unanticipated) emergency events are those that emergency responders need to react immediately without time to prevent or prepare for the impact of the event. Examples of these types of events are tornadoes, earthquakes and even human-caused events such terrorist attacks. In this research investigation, the scope is limited to unexpected emergency situations, but we are confident that the work is also applicable for anticipated emergencies with certain minor modifications.

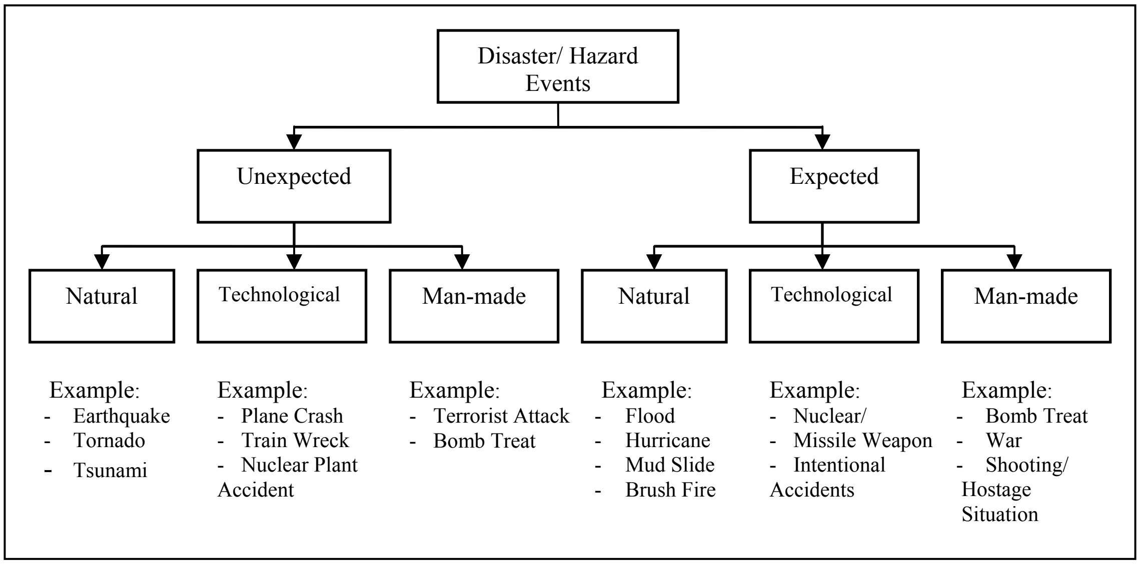


Figure 1.4. Categories of disaster and hazards events by expectation (FEMA, 2006).

1.4 Emergency Evacuation Time

During an emergency evacuation, the time required to evacuate is of utmost importance, and it is one the main factors one should consider when developing a plan for evacuation. In this research evacuation time includes the time required to configure all traffic control elements on the evacuation routes, initiate the evacuation, and clear the routes of vehicles once all evacuating vehicles reach a destination of safety. Here, evacuation time does not include the time needed for local officials to assemble and make a decision to evacuate. Evacuation time during expected and unexpected emergency events is different. In general, evacuation time in both expected and unexpected are actually composed of three time subcomponents – mobilization time, travel time and queuing delay time (see Figure 1.5). As shown in Figure 1.5, for expected emergencies, mobilization time is larger and the queuing delay time is shorter due to the larger time window for planning and completing the evacuation. On the other hand, the unexpected emergencies have a shorter time window for evacuation. As a result, the time to mobilize evacuees and responders is shorter and the queuing delays at merge and cross points are longer. The amount of time required for clearance can be significantly lengthened by route congestion and the setup time required for more complex control elements such as those required for contraflow lane reversals.

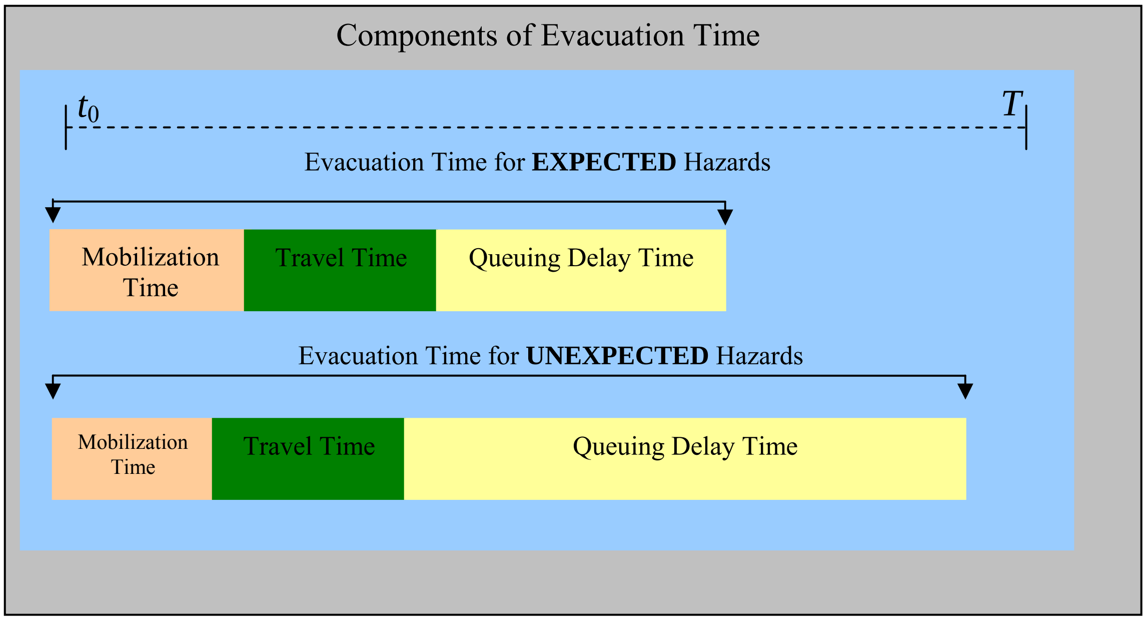


Figure 1.5. Components of evacuation time (adapted from Florida Disaster (2000)).

1.5 Current Practices and Challenges of Evacuation Planning

Historically, evacuation planning and execution has been the responsibility of emergency management and law enforcement agencies. While some state transportation agencies have contributed to the evacuation planning and management process, their activities are usually characterized as peripheral support (Tufekci, 1995). FEMA requires all states to have a comprehensive emergency operations plan. These plans guide emergency operations for all types of hazards, from natural to technological to man-made. While the evacuation issues faced by coastal states are similar, the specifics of their plans differ since their geographic and transportation system characteristics vary widely (Wolshon *et al.*, 2001). However, contraflow lane reversing is a common practice among the states.

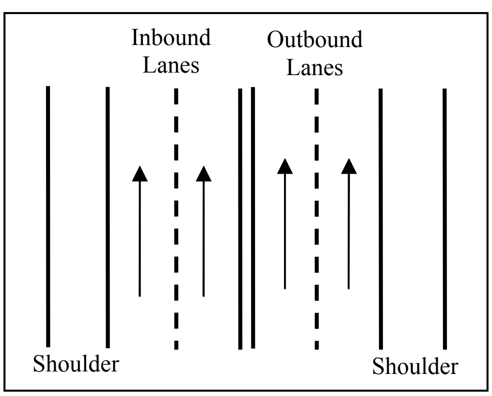
1.5.1 Contraflow Lane Reversals

Contraflow lane reversals alter the normal flow of traffic, typically on a controlled-access highway to aid in an emergency evacuation. Travel lanes that are normally only configured for travel in one direction are reconfigured so that the normal flow direction is reversed. This increases the effective lane capacity for evacuation traffic flow. Capacity of a lane is defined as the number of vehicles per hour. All incoming flow on the reversed lanes is blocked until the end of the contraflow program execution.

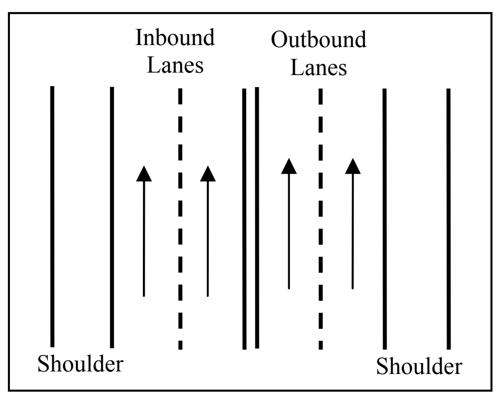
Implementation of contraflow lane reversals is generally resource-intensive as it requires a significant number of law enforcement officers and other officials to manually direct traffic during a lane reversal, especially at intersections and interchanges. When contraflow lane reversals are performed, each entrance ramp of the opposite direction of the traffic is blocked by uniformed officers and each exit ramp is temporarily converted to an entrance ramp. Also, pilot vehicles drive each section of the evacuation route to make sure that no vehicles are inadvertently trapped in a section of the roadway. If this is not done, vehicles could be met by outbound evacuation traffic (Wolshon *et al*., 2001). Contraflow lane reversal programs also lack proper signage, signals and other traffic control devices needed to conduct traffic in the opposite direction.

There are several different contraflow lane reversal configurations. For instance, assume a four-lane roadway where there are two inbound lanes and two outbound lanes (as shown in Figure 1.6). Figure 1.6(a) illustrates the roadway under normal operation. Figure 1.6(b) shows all inbound lanes reversed to outbound lanes resulting in four outbound lanes for evacuees to utilize. Figure 1.6(c) shows one inbound lane reversed to an outbound lane. Therefore, there are three outbound lanes that can be utilized by evacuees, and the inbound lane will be maintained for inbound traffic. Typically, under voluntary evacuation, emergency service vehicles and people who want to move against the evacuating traffic use the single inbound lane. This type of reverse-laning increases the potential of accidents. However, under mandatory evacuation, the single inbound lane is used only by emergency service vehicles. Figure 1.6(d) shows one inbound lane reversed with the shoulder used as additional outbound lane capacity for evacuees. The most common lane reversal configuration is when all inbound lanes are reversed to the outbound direction, since it is the most one increases the capacity (*i.e.*, vehicles per hour per lane) the most with the least confusion (Pal *et al.*, 2005; Wolshon *et al.*, 2001). We consider only this contraflow lane reversal strategy in this research.

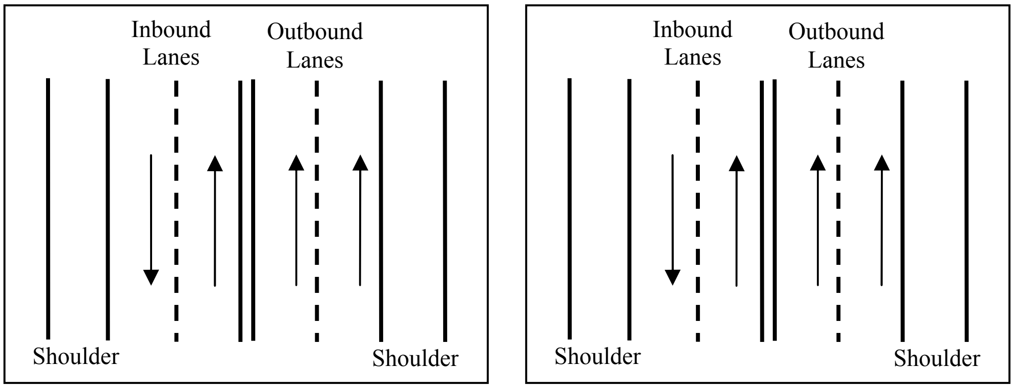
The decision-maker who specifies when and what type of reverse-laning program to execute varies from state to state. For example, in Louisiana, the Governor is responsible for starting and ending the contraflow lane reversal operation. In Florida, the Governor starts the reverse-laning operation, but the Florida Highway Patrol ends the operation.



(a) Normal lane directions – two outbound lanes and two inbound lanes



(b) All inbound lanes reversed to outbound lanes.



(c) One lane inbound reversed to an outbound lane.

(d) One lane reversed to an outbound lane and use of the roadway shoulder.

Figure 1.6. Types of contraflow lane reversal roadway configurations (adapted from Wolshon et al. (2001)).

1.5.2 Interaction between Evacuee Flow and Responder Flow

Current contraflow lane reversal programs traditionally focus on evacuee flow. However, several factors directly affecting evacuee flow behavior should also be considered. In particular, emergency responder flow moving towards the hazardous area should also be considered in emergency evacuation route planning. This is especially the case in unexpected emergency events.

Citizens who remain in the hazardous areas prepare for the hazard event by purchasing and pre-positioning different supplies, especially in mandatory emergency evacuations. Governmental and law enforcement officials occupy roadways for the purposes of securing areas where an emergency evacuation order has been issued. As a result, evacuee flow and emergency responder flow occupy roads on the evacuation network configuration simultaneously.

In an emergency situation, two simultaneous, heterogeneous opposing flows can exist. The first flow is vehicular flow of evacuees from the source of a hazard to destinations of safety. The second flow is the flow of emergency officials (*i.e.*, first responders) to the hazard source.

These two flows traverse a bi-directional capacitated travel network where the travel lanes and the merge and cross points are fixed. It would be more efficient to develop routing plans that consider both flows simultaneously, since each flow will impact the other.

1.6 Objectives of This Research Investigation

The objectives of this research are to:

(1) Formulate the multiple flow EERP problem in the presence of an unexpected emergency event that requires a large-scale evacuation; In addition to the introduction, formulation and discussion of the multiple flow EERP problem, the contribution of this research is an approach that serves as the initial effort to solve this practical problem; and

(2) Develop a solution approach that is capable of rapidly generating evacuee routes and emergency first responder routes during times of mandatory evacuations.

Two key components of evacuation behavior that are considered are:

- There exist two heterogeneous flows (evacuees and emergency first responders); these two flows are assumed to be incompatible, and by incompatible, it is meant that the two different flows cannot occupy a given travel lane or a merge or cross point at the same time; and
- Contraflow lane reversals are allowed.

1.7 Expected Contributions of This Research Investigation

Due to increase of natural, man-made and technological disasters, more specifically unexpected emergencies requiring large-scale evacuations, there is a serious need for an efficient emergency evacuation route planning methods. 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. There is no previous work done on the EERP problem where both evacuee and responder flows are considered simultaneously. Furthermore, this research considers contraflow lane reversals, which is a practice most states in the US apply during large-scale emergency evacuations.

The primary contribution of this research is that it serves as the initial efforts to formulate and solve the emergency evacuation route planning problem considering two heterogeneous flows that occur simultaneously during evacuation. Also, in this research, the network roadway configuration where contraflow lane reversals are allowed is identified, including the time schedule the lane reversals occur. The consideration of these characteristics simultaneously for EERP has not received noticeable attention to date. Therefore, this research potentially contributes quite significantly to the body of knowledge in the area of emergency management and disaster planning.

1.8 Overview of This Dissertation

The remainder of this dissertation is organized as follows. CHAPTER 2 summarizes the current research literature that addresses the emergency evacuation route planning problem. This problem has been addressed using analytical mathematical programming models, queuing models and simulation models. In CHAPTER 3, four incremental integer linear programming model formulations for the EERP problem are presented. Three of these models have not been formulated before in the current literature. These three model formulations lay the foundation for research in an area that has been gaining increasing attention in recent years. Specifically, the models, which consider simultaneous, heterogeneous network flows and contraflow lane reversals, are a primary contribution of this research. Computational results are presented after applying the models to a real-world dataset. CHAPTER 4 presents a proposed genetic-based heuristic approach for the EERP. Lastly, CHAPTER 5 summarizes the research, followed by a discussion of the plans for future research that extends the research described in this dissertation.

CHAPTER 2:
LITERATURE REVIEW

2.1 Introduction

Chapter 1 highlights the need for the further study and development of emergency evacuation route planning (EERP) models and highlights some real-world characteristics that should be investigated. This chapter focuses on previous work on EERP. The literature on emergency evacuation models can be divided into two main categories: analytical models and simulation models (see Figure 2.1). The literature covers both the modeling of evacuees and the emergency responders. Both static and dynamic models have been developed, where static models are those that only model a snapshot of the travel network and dynamic models include those models that consider the changing nonlinear conditions within the network over time.

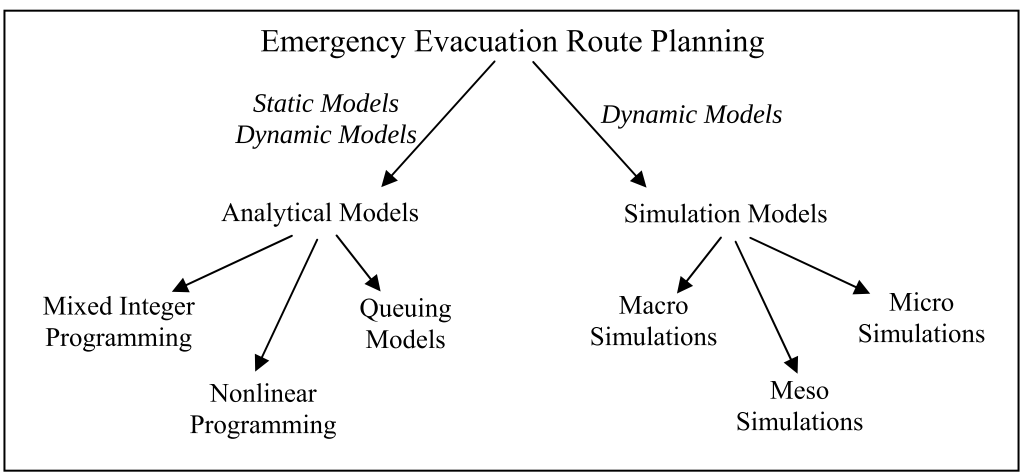


Figure 2.1. Categories of existing emergency evacuation route planning models.

2.2 General Network Optimization Models Related to Route Planning

Major research in the area of traffic flow optimization has its beginnings in the 1960's. During this time, researchers started investigating different methodologies for network optimization when determining the shortest path between an origin and a destination. A network is generally defined as a graph $G(\mathbf{N},\mathbf{A})$, where **N** is a set of nodes, and **A** is a set of arcs where each arc connects a pair of nodes i and j in **N**. An arc (i,j) can be either bi-directional or unidirectional and associated with each arc (i,j) is a cost c_{ij}, typically a non-negative number.

One problem that relates directly to the EERP is the shortest path problem. The objective function in shortest path problem is to find the shortest route from the origin to the sink in a directed connected network. Some early work on the shortest path problem includes that of Elmaghraby (1970), Yen (1971) and Petersen (1975). In more recent work, Avella *et al.*, (2002) propose a heuristic solution for the resource-constrained shortest path problem. It is used to design the paths of the planned missions of centrally-controlled low emission vehicles. Rego (1998) presents the subpath ejection chain method for the vehicle routing problem under route length and capacity restrictions. They do not consider dynamic flow based on time. Azaron and Kianfar (2003) use stochastic dynamic programming to find the dynamic shortest path from the source to sink. The model assumes that arc lengths of the stochastic dynamic network are independent random variables with exponential distributions, and each node except the sink node is an environmental variable that evolves with a continuous time Markov process.

There are other network routing problems that are closely related to the EERP. The minimum spanning tree (MST) problem is similar to the shortest path problem, as both consider a directed connected network. The objective of MST is to minimize the total length of the inserted links in the network. The maximum flow problem considers directed connected network, in order to maximize the flow through the network. The minimum cost flow problem considers directed connected network with at least one supply node and one demand node. Its objective is to minimize the total cost of sending the available supply through the network to satisfy the given demand.

Other significant bodies of related work are the vehicle routing problem (VRP) and the traveling salesperson problem (TSP). The VRP is a problem that designs routes for the vehicles in order to meet the given constraints and minimize a given objective function (*e.g.*, total travel distance, number of vehicles, or total travel time). The VRP features a set of depots (number, location), a set of vehicles (capacity, costs, time to leave, driver rest period, type and number of vehicles, max time), a set of customers (demands, hard or soft time windows, pickup and delivery, accessibility restriction, split demand, priority), and route information (maximum route time or distance, cost on the links).

The TSP finds the route of visiting all cities in a given collection of cities that minimizes the total cost of travel between the cities. VRP is a generalization of the TSP where the TSP is a VRP with one vehicle with no capacity limits, no depot, and customers with no demand. Table 2.1 summarizes the problems related to the EERP problem.

Table 2.1. Network problems related to the EERP problem (Hiller and Lieberman, 2001).

Problem Type	**Objective**
Maximum Flow	Maximize the total amount of the flow through the network
Minimum Cost Flow	Minimize the cost of sending the available supply through the network satisfying the demand
Shortest Path	Find the *n*th nearest node to the origin
Minimum Spanning Tree	Minimize the total length of the links inserted into the network
Traveling Salesperson	Minimize length route with the minimum cost

2.3 Emergency Evacuation Route Planning Modeling

The body of previous research related to emergency evacuation route planning is now reviewed. This research can be segmented into two primary areas. The first is emergency evacuation modeling where evacuees are traveling from a hazard source to safe destinations. The majority of research in this area is from this perspective. The second major area of EERP research is routing emergency first responders from other originations to the hazard source (Azaron and Kianfar, 2003).

2.3.1 Analytical Models for Emergency Evacuation Route Planning

Church and Cova (2000) propose a new specialized network partition model called the critical cluster model (CCM). It identifies small areas that have high ratios of population to exit capacity and maximizes bulk lane demand or an estimate of network clearing time. They formulate the problem as a nonlinear optimization problem. Cova and Johnson (2003) develop a network flow model for identifying optimal lane-based evacuation routing plan in a complex network that consists of intersection conflicts by using a minimum cost flow approach. They derive an optimal routing plan for a sample network after formulating the problem as a mixed integer programming problem. The objective of their model is to maximize the flow of evacuees from a source to a destination through a lane-based network, and minimizing total evacuees, travel distance. They focus on eliminating the cross conflict points, and minimizing the merging points at the intersections. Reducing the number of crossing points and merging points in an evacuation will decrease the total travel time of the evacuees, which is another objective that has to be considered.

More recently, Yi and Ozdamar (2006) develop a mixed integer multi-commodity network flow model. It coordinates logistics support (dispatching commodities) and evacuation operations in disaster response activities. Although their model is an essential one for disaster management, they do not consider the outflow traffic that is dependent on the inflow (emergency first responder) traffic. Shekhar and Kim (2006) develop a linear programming model to find the configuration of the travel network for evacuee outbound flow. The objective is to minimize the travel time of evacuees. They successfully develop two heuristics that minimize evacuee evacuation time.

A large part of the previous work on evacuation routing modeling uses queuing models, more specifically, $M/M/1$ and $M/M/C$ models. For instance, Smith (1991) considers the dynamic conditions in real-world emergency evacuation situations by presenting state-dependent queuing models that capture the nonlinear effects of increased occupant traffic flow along emergency evacuation routes. The state-dependent queuing modeling approach considers $M/M/1/K$, $M/M/C/K$ and $M/G/C/C$ models. Bakuli and Smith (1991) extend the work of Smith (1991) in state-dependent queuing models and study resource allocation in state-dependent emergency evacuation networks.

Baykal-Gursoy *et al*. (2004) develop a model of traffic flow on a two-lane roadway link that is subject to traffic incidents. They model it as a steady-state $M/M/C$ queuing system where they consider C servers that are subject to random interruptions that are exponentially-distributed. The authors assume that service times are independent and exponentially-distributed with mean μ, and clearance times are independently and exponentially-distributed with mean r. Interruption arrivals, vehicle arrivals, and the service and clearance times are all assumed to be mutually independent. They develop a mathematical model after they define the stochastic process that describes the state of the link at time t and use Little's Theorem to compute average travel time. Figure 2.2 shows the relation between the expected numbers of evacuee vehicles versus the service rate. The authors suggest that the stationary number of vehicles on the link when no accidents occur (the bottom-most curve) constitutes the lower bound. They also state that if the service rate does not change, higher traffic incident frequency or a slower clearance rate would lead to more vehicles on the link.

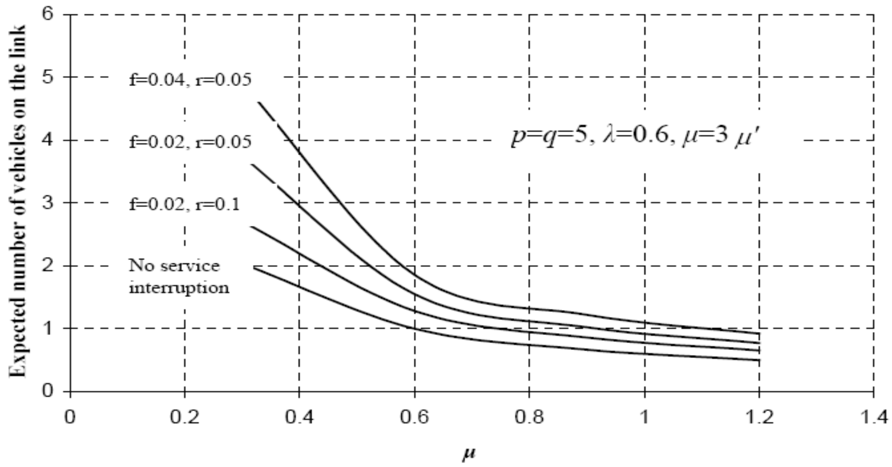


Figure 2.2. The relation between the expected number of vehicles versus the service rate (obtained from Baykal-Gursoy *et al*. (2004)).

2.3.2 Simulation Models for Emergency Evacuee Route Planning

The other and seemingly preferred approach in emergency evacuation route planning is simulation modeling. Simulation is more of a passive approach to route planning in that it is primarily used to evaluate candidate routing plans. Pidd *et al.* (1996) and Schreckenberg *et al.* (2001) discuss different spatial scales used to simulate traffic flow. Table 2.2 summarizes different types of simulation models that they discuss.

Table 2.2. Types of simulation models that have been used for emergency evacuee route planning (summarized from Pidd *et al.* (1996) and Schreckenberg *et al.* (2001)).

Simulation Model	**Description**
Macrosimulation	• Does not track the detailed behavior of individual entities; uses dynamic state equations that are analogous to those for fluid flows in networks. • Main advantage is that it is less computationally-demanding than are microsimulators
Microsimulation	• Simulates single vehicles. • Since the simulation of single entities requires a higher computational effort, an efficient modeling of traffic flow must be achieved by a minimum set of parameters and large time steps. • Entities move from the evacuation zones and proceed to safe destinations, either by their own route finding or under police or martial control.
Mesosimulation	• Compromise between the macrosimulation models and microsimulation models • Usually involve a discrete event simulation, which tracks the movements of groups of vehicles

SheffI *et al.* (1982) model the flow pattern during the evacuation of areas surrounding a nuclear power plant. The authors consider the time required to transport and manage flow on the travel network. The model is sensitive to the network topology, intersection design and control, and a wide array of evacuation management strategies.

Tufekci and Kisko (1991) develop a regional emergency evacuation simulation modeling system (REMS) that integrates optimization models with simulation models. More specifically, the modeling system uses simulation as well as several network optimization models in estimating the evacuation time and the traffic flow on a given transportation road network. Tufekci (1995) extends this work and integrates the REMS with a decision support system applying the integrated approach to hurricane emergency management with positive results. Rathi and Solanki (1993) also develop a computer simulation modeling system called Oak Ridge

Evacuation Modeling System (OREMS) of traffic flow that estimates the time it takes vehicles to evacuate a region. OREMS consists of a set of three computer programs: ESIM, a network traffic flow simulation model; IEVAC, an interactive graphical input data manager for ESIM; and SIMOD, interactive graphical output display software for ESIM.

Sinuany-Stern and Stern (1993) construct a behavioral-based simulation model to examine the sensitivity of network clearance time to several traffic factors. They investigate the interaction with pedestrians, intersection traversing time, and car ownership and route choice mechanisms. They use microscopic simulation to model the series of events during a radiological emergency situation.

Franzese and Joshi (2002) consider the effect of real-time information of network congestion on evacuation routes occupied by vehicles that supply goods from distribution centers to stores. They consider the congestion in the network that may arise during peak demand. A traffic simulation model is developed in order to mimic the actual traffic conditions as a function of times of the day. They focus on recurrent congestion which is congestion caused by the relationship between traffic demand and capacity.

Tuydes and Ziliaskopoulos (2004) develop a mesoscopic network evacuation model based on a dynamic traffic assignment method. Their proposed model optimizes the system travel time, and computes the optimal capacity reversibility in the network. Although they optimize their problem mathematically, they use small-scale experiments (*i.e.*, networks with less than 50 nodes). Although their model identifies optimal reversibility designs for large-scale networks that reduce total system travel time, it considers only outflow traffic.

2.4 Emergency First Responder Flow Modeling

2.4.1 Analytical Models of Emergency First Responder Routing

Larson (1974; 1975) studies the behavior of emergency responders as a multi-server hypercube queuing system with distinguishable servers. He uses the $M/M/C$ queuing model in which the server is selected randomly, and C is the number of servers. He develops this model to solve problems of locating ambulance vehicles, configuring the response district in emergency services areas, and balancing the workload. His model assumes also that all units have the same amount of exponentially-distributed service demand, and they cover the same areas. However, such an assumption is not valid under emergency evacuation conditions. Larson and Franck (1978) modify the hypercube queuing model of Larson (1974) by adding a Markov process model. They develop a computer-implemented analytical model that serves as an evaluation tool for automatic vehicle location systems. In their implementation, the model focuses on computation and storage in order to minimize the procedure for generating the state-to-state Markov transition rates. Their model has the same fixed demand assumption as that in Larson (1974; 1975).

Chiu and Larson (1985) develop a model to locate a facility to service a region. There are n mobile servers in one facility that will respond to emergencies. The model assumes that servers are available all the time, and that the service time is exponentially-distributed. The objective function is to locate a single garage facility for n servers in order minimize the expected weighted cost of travel time and cost of lost customers.

Daskin and Stern (1981) formulate a hierarchical objective set covering problem for locating minimum number of emergency medical service vehicles needed in a maximum zone possible. They assign at least one vehicle for each zone disregarding the workload. Therefore, their model is not flexible since each zone is assigned one vehicle without considering the workload of that zone.

2.5 Integration of Analytical Models and Simulation Models for Emergency Evacuation Route Planning

Several approaches to evacuee route planning that integrate both analytical models and simulation models have been proposed (*e.g.*, Swoveland *et al.*, 1973; Tufekci and Kisko, 1991; Yi and Ozdamar, 2006). Swoveland *et al.* (1973) construct an ambulance planning model using a branch and bound technique with simulation to generate an optimal plan to locate an ambulance with minimum response time. Input to the simulation model is a travel-time matrix (time needed from node to node), routing matrix (shortest route from node to node), region definitions, ambulance locations, dispatch rule and a call stream.

Takeda *et al.* (2005) study the hypercube queuing model of the urban Emergency Medical Service of Campinas in Brazil. In its original configuration, all ambulances are located in a central location. They analyze the effects of decentralizing ambulances and adding new ambulances to the system, comparing the results to those of the original situation.

Although beyond the scope of this research investigation, building evacuations during emergency situations are modeled similar to emergency evacuations on roadways. There are two kinds of models used in developing emergency evacuation routing plans for buildings – analytical models (*e.g.*, Chalmet *et al.*, 1982; Jarvis and Ratlife, 1982; Choi *et al.*, 1988; Lovas, 1995) and simulation models (*e.g.*, Jain and McLean, 2003; Hanisch *et al.*, 2003).

2.6 Metaheuristic Approaches for Emergency Evacuation Modeling

Several researchers have successfully integrated heuristic optimization procedures with analytical and simulation models to improve solutions. For instance, Davies and Lingras (2003) propose the Genetic Algorithm for Rerouting Shortest Path (GARSP) method. They consider a dynamic network where the network is adaptable to any new time-based information and can generate new routes based on the information.

More recently, Ceylan and Bell (2005) propose a GA-based approach, called Genetic Algorithm TRANSYT and Path Flow Estimator (GATRANSPFE), to solve a slightly different traffic flow problem. They consider the upper-level problem for a signalized road network under congestion. Stochastic user equilibrium traffic assignment is applied at the lower-level. At the upper-level, the GA provides a feasible set of signal timings within specified lower and upper bounds on signal timing variables and feeds into the lower-level problem. The problem occurs when the demand exceeds the capacity, which causes an increase in green light timings at a signalized junction.

GATRANSPFE in all levels of demands is compared with a mutually consistent (MC) solution. The MC solution is from a MC model that is a formulation of combined traffic assignment and area traffic control. Under different levels of demand, the results show that GATRANSPFE systematically performs 100% better than the MC model. Also, GATRANSPFE shows less sensitivity to the increasing traffic load and demand as compared to the MC solution.

2.7 Summary and Conclusions

In summary, the existing literature is rich with work on the emergency evacuation routing problem. Closer examination of the previous work shows that the majority of the literature can be divided into two parts: analytical modeling and simulation modeling. Several analytical and simulation models of emergency evacuation routing work have been proposed. However, there are issues that have not been considered and still remain to be investigated.

The existing analytical models and simulation models do not consider simultaneous, opposing heterogeneous flows with contraflow lane reversals. In an emergency situation, there are two flows – an inbound flow of emergency responders and an outbound flow of evacuees (vehicles and pedestrians). In a mandatory emergency evacuation, all evacuee traffic flow moves away from the hazard source. However, there is an opposing flow that moves toward the hazard source. Therefore, an emergency evacuation routing plan should consider the two flows, since one would impact the other. Previous work does not consider emergency responder (ambulance, medical services, facility allocation, *etc*.) and emergency evacuee route planning simultaneously, for any kind of hazard (*i.e.*, natural, man-made and technological) occurrence.

CHAPTER 3: MODELING THE EMERGENCY EVACUATION ROUTE PLANNING PROBLEM

3.1 Introduction

In this chapter, a number of formulations of the emergency evacuation route planning (EERP) problem are proposed. A review of the EERP literature reveals that researchers either focus on evacuee flow or focus on emergency responder flow. However, in an emergency situation, at least two simultaneous, heterogeneous, opposing flows can occur. The first is the flow of evacuees from the impacted areas to destinations of safety. The second flow is the flow of emergency officials (first responders) to the impacted areas. These two flows traverse a bi-directional capacitated transportation network where the roadway segments (arcs) and merge and cross points (nodes) are fixed. In this research, we consider a special case of the EERP problem where we examine a transportation network in the presence of these two flows and assume these two flows are incompatible. By incompatible, we mean that the two different flows cannot occupy a given link or node at the same time. Furthermore, we model contraflow lane reversals as they are often utilized in practice to reduce congestion and increase outbound capacity during evacuations in disaster situations (*e.g.*, hurricanes). Evacuation planners and decision-makers have no recognized guidelines for the operation and design of the contraflow roadway segments (Wolshon *et al.*, 2001). To the best of our knowledge, this is the first treatment of the EERP problem that considers both evacuee and responder flows simultaneously. Previous EERP work typically models only unidirectional evacuee flow only from the source of a disaster to destinations of safety or only unidirectional emergency official flow to the disaster source.

3.2 The Multiple Flow Emergency Evacuation Routing Planning Problem

In this section, we address four EERP problems and propose mathematical formulations for each. The first EERP problem is the general single-flow evacuee problem. This problem is one that has been addressed by past researchers and considers only the flow of evacuees. The second problem we consider is the single-flow evacuee problem where roadway direction reversals (*i.e.*, contraflow lane reversals) are allowed. The third EERP problem we address is the two-flow evacuation problem in which no contraflow lane reversals are allowed. The last problem addressed is the two-flow emergency evacuation route planning problem under contraflow conditions. In this research, the EERP problem is formulated as a maximum flow problem, which is reasonable for this type of problem. Then, the four EERP problems are formulated as integer linear programming (ILP) models. Before presenting the models and the proposed formulations, the general EERP problem is described.

3.2.1 General Formulation of the EERP Problem

Evacuation route planning is the common process of moving citizens (evacuees) in a hazardous area to areas of safety in emergencies. We formulate the general EERP problem as follows. Let a directed graph $G(\mathbf{N},\mathbf{A})$ represent the network representation of the geographic region of interest that consists of state highways, state and county roads, along with intersections and relevant sites in the region under consideration. $\mathbf{A}$ is the set of arcs that represents lane-based interstate and arterial roadways. 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 $\mathbf{N}_D$, *i.e.*, $\mathbf{N} = \mathbf{N}_S \cup \mathbf{N}_T \cup \mathbf{N}_D$. The intermediate nodes represent where evacuee flow merges or crosses. Each arc in $\mathbf{A}$ is expressed as arc (i,j), which is the arc that connects nodes i and j. We call this a static network since each arc in the network represents a stationary link from one node in the network to another. $\mathbf{X}_E \subset \mathbf{N}$ is the set of nodes representing the locations occupied by evacuees.

Associated with each arc and node is a number of parameters. Each node k represents a location in the network with an initial population p_k and a capacity v_k. For each arc (i,j), we associate a capacity c_{ij}, where arc $(i,j) \in \mathbf{A}$. The capacity of an arc is the maximum flow per unit of time, assuming no congestion. In the case of a lane-based roadway network, capacity is the number of vehicles per hour per lane. For each arc, a travel time τ_{ij}, where arc $(i,j) \in \mathbf{A}$. Here, it is often assumed that τ_{ij} is constant and is the mean speed to traverse arc (i,j) when the arc is free of evacuees. This parameter is often referred to as the free flow speed or lead time for arc (i,j). The term x_{ijt} is the number of evacuees that move from node i at the beginning of period t to node j at the end of period t. The objective is to maximize the flow of people away from the source node to the sink node as rapidly as possible.

Claim 3.1: (Lower Bound) The lower bound on network clearing time is the sum of the arc lead times starting from the nodes closest to the hazard source to the destination node farthest from hazard source. If Node 1 is the source node connecting all nodes closest to the hazard source, and None N is the farthest destination node, the lower bound can be calculated as

$$F_{1,N} = \sum_{(i,j)\in\mathbf{A}} \tau_{ij} \quad \forall i, j \text{ where } i \neq j \,. \tag{3.1}$$

Typically, arc capacities, which represent the number of evacuees that can traverse a given arc per unit time, are often assumed to be constant. However, realistically, the capacities of arcs are not constant. In fact, the capacity on a given arc is a function of the number of entities present on that arc at a given time. Incorporating the flow-dependent capacities converts the corresponding network flow problems into network flow problems with side constraints, which is not the focus of this current research. However, this problem is worthy of further study.

3.3 The Single-Flow EERP Problem

In this section, we address two single-flow EERP problems for unexpected emergency events. First, we formulate an ILP for what we call the base problem, which is the single-flow EERP problem with normal flow. Normal flow is the flow of evacuees in the normal flow direction of the arcs. Then, the single-flow problem where contraflow lane reversals are allowed is addressed. The objective for this problem is to not only maximize the flow of entities through the network to the destination nodes but also to reconfigure the travel network using contraflow lane reversals where appropriate. Before presenting the EERP problem formulations, a number of modeling assumptions are presented.

Modeling Assumptions:

- There is one super source node and one super sink node for evacuees;
- There is one super source node and one super sink node for emergency responders;
- 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*;
- The lead time on a given arc τ_{ij} is deterministic and known with certainty;
- The lead time on a given arc is not a function of the number of entities present on that arc;

- There is no limit on the number of arcs in the travel network to which contraflow lane reversals can applied; and
- There is no restriction on the number of times the flow direction on a single arc can be changed during the active period of the evacuation.

3.3.1 Single-Flow EERP Problem with No Contraflow Lane Reversals

In a travel network under emergency conditions, there are multiple starting locations from which populations of evacuees flee. In addition, there are multiple destinations of safety to which the evacuating citizens flee. Therefore, in the EERP problem, multiple source nodes and multiple sinks must be considered. To address such a network structure in order to model the problem as a maximum flow problem, the travel network is modified accordingly. In other words, a dummy node is created to serve as a super source node that feeds the multiple source nodes. In addition, a dummy node is created to serve as a super sink node that receives all flow from the set of sink nodes. The expanded network has the required single source and single sink and is suitable for the maximum flow problem. The capacity of both the super source and super sink nodes is set greater than or equal to the total number of entities to move to the nodes. Furthermore, the capacity of the set of arcs emanating from the super source node and set of arcs terminating at the super sink node is set to the maximum flow, and the lead time on these arcs is equal to zero. For illustration, a simple unidirectional evacuation network is shown in Figure 3.1. The red Node 1 is the single super source node, and the green Node 6 is the single super sink node.

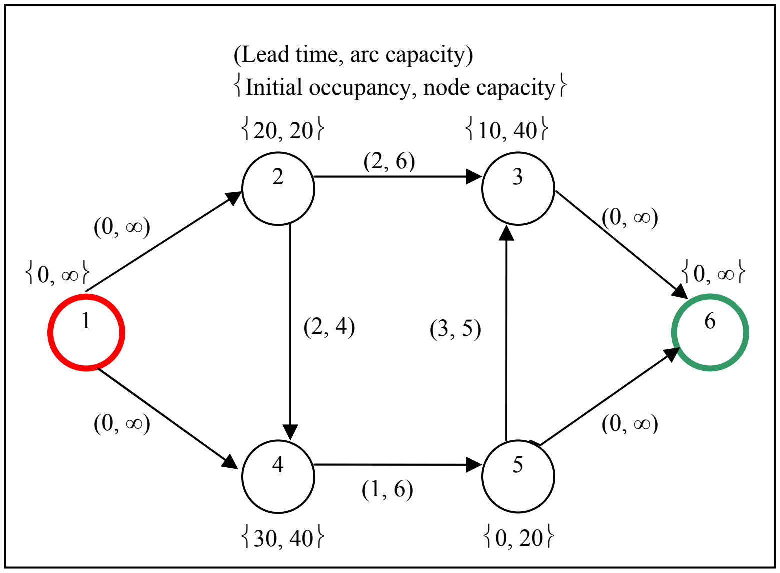


Figure 3.1. Example of a single-flow evacuation network under normal flow conditions.

The problem parameters, decision variables, objective function and constraints of the general single-flow EERP problem with no contraflow are as follows:

<u>Problem Parameters:</u>

T : Total number of periods to clear the transportation network

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

p_{k0} : Population of evacuees at node k ($k = 1, \ldots, N$) in the network before evacuation begins

v_k : Capacity of node k ($k = 1, \ldots, N$) in the network

c_{ij} : Capacity of arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$ where $i \neq j$) in the network

τ_{ij} : Free flow time on arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$ where $i \neq j$) in the network

Primary Decision Variable:

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

Secondary Decision Variables:

p_{kt} : Population of evacuees at node k (k = 1, …, N) in the network at the end of period t

O_t : Number of evacuees who clear the network at end of period t

$$\max \quad Z = \sum_{t=1}^{T} (T + 1 - t) O_t \tag{3.2}$$

$$\text{s.t.} \quad O_t = \sum_{i=1}^{N-1} x_{iNt} \qquad \forall t = 1, \ldots, T \tag{3.3}$$

$$p_{k1} = p_{k0} - \sum_{j=1}^{N} x_{kj1} \qquad \forall k = 1, \ldots, N\text{-}1 \tag{3.4}$$

$$p_{kt} = p_{k(t-1)} - \sum_{j=1}^{N} x_{kjt} + \sum_{i=1}^{N} x_{ik(t-\tau_{ik})} \qquad \forall k = 1, \ldots, N;\ t > 1 \tag{3.5}$$

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

$$x_{ijt} \leq c_{ij} \qquad \forall i, j = 1, \ldots, N;\ i \neq j;\ \forall t = 1, \ldots, T \tag{3.7}$$

$$x_{ijt} \geq 0, \text{ integer} \qquad \forall i, j = 1, \ldots, N;\ i \neq j;\ \forall t = 1, \ldots, T \tag{3.8}$$

The objective function Eq. (3.2) maximizes the number of evacuees exiting the network, which is multiplied (weighted) by t (t = 1, …, T), by routing the evacuees to destinations of safety (represented by the final node N) early in the time interval 1 to T. Eq. (3.3) sums for each period t the total number of evacuees that reach the final node N from each node i connected to node N. Eqs. (3.4) and (3.5) ensure the conservation of flow at each node for the first period and for the subsequent periods, respectively. Eqs (3.6) and (3.7) enforce the capacity constraints for the nodes and arcs, respectively. Eq. (3.8) is the non-negativity and integrality constraints.

3.3.2 Single-Flow EERP Problem with Contraflow Lane Reversals

For the single-flow EERP problem with contraflow, we modify the model for the base problem so that it finds a reconfigured network and identifies the best direction for each arc to maximize the flow of evacuees out of the network. The proposed model reverses the travel arcs and reallocates the available arc capacity in the network. Figure 3.2 shows the normal flow directions (the solid arcs) and the contraflow directions (the dashed arcs) for a transportation network.

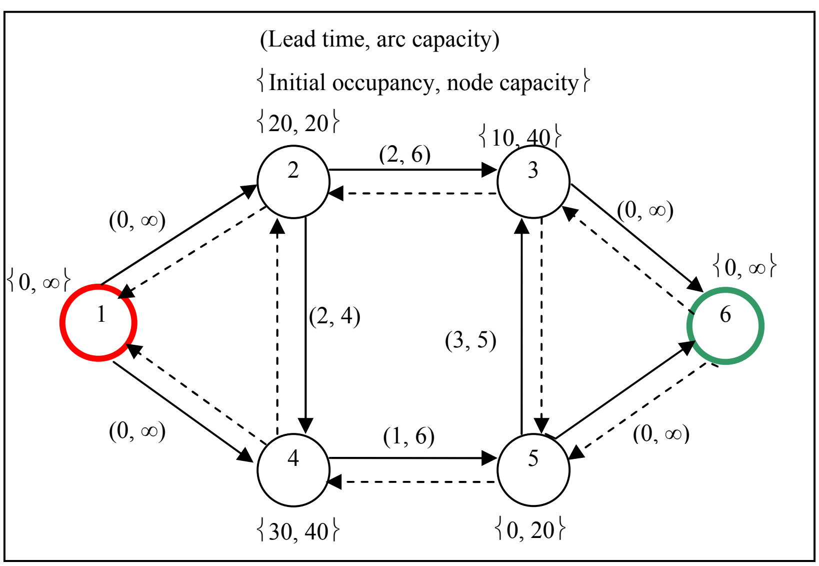


Figure 3.2. Example of single-flow evacuation network with normal flow and contraflow directions.

Problem Parameters:

T : Total number of periods to clear the transportation network

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

p_{k0} : Population of evacuees at node k ($k = 1, \ldots, N$-1) in the network before evacuation begins

v_k : Capacity of node k ($k = 1, \ldots, N$) in the network

c_{ij} : Capacity of arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$, where $i \neq j$) in the network

τ_{ij} : Free flow time on arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$, where $i \neq j$) in the network

Primary Decision Variables:

x_{ijt} : Evacuee flow from node i at beginning of period t (end of period t-1) to node j at end of period t (beginning of t+1)

y_{ijt} : Evacuee contraflow from node i at beginning of period t (end of period t-1) to node j at end of period t (beginning of t+1)

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

Secondary Decision Variables:

p_{kt} : Population of evacuees at node k ($k = 1, \ldots, N$-1) in the network at the end of period t

O_t : Number of evacuees who clear the network at end of period t

$$\max \quad Z = \sum_{t=1}^{T} (T+1-t) O_t \tag{3.9}$$

$$\text{s.t.}\quad O_t = \sum_{i=1}^{N-1} x_{iNt} + \sum_{i=1}^{N-1} y_{iNt} \qquad \forall t = 1, \ldots, T \tag{3.10}$$

$$p_{k1} = p_{k0} - \sum_{j=1}^{N} x_{kj1} + \sum_{j=1}^{N} y_{jk1} \qquad \forall k = 1, \ldots, N\text{-}1 \tag{3.11}$$

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

$$p_{kt} \le v_k \qquad \forall k = 1, \ldots, N;\ \forall t = 1, \ldots, T \tag{3.13}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} x_{ijt} \le c_{ij} e_{ijt} \qquad \forall t = 1, \ldots, T;\ i \ne j \tag{3.14}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} y_{jit} \le c_{ij} \left(1 - e_{ijt}\right) \qquad \forall t = 1, \ldots, T;\ i \ne j \tag{3.15}$$

$$x_{ijt} \ge 0,\ \text{integer} \qquad \forall i, j = 1, \ldots, N;\ i \ne j;\ \forall t = 1, \ldots, T \tag{3.16}$$

The objective function Eq. (3.9) maximizes the number of evacuees exiting the network at each time period t ($t = 1, \ldots, T$) by routing the evacuees to destinations of safety (represented by the final node N) early in the time interval 1 to T. Eq. (3.10) sums for each period t the evacuees that reach the final node n from each node i connected to node N using both normal flow and contraflow. Eq. (3.11) and Eq. (3.12) ensure the conservation of evacuee flow constraints for the first and subsequent periods by including the contraflow to the normal flow that are exiting and entering each node. Eq. (3.13) is the node capacity constraint. Arc capacity constraints ensure that only one type of flow (normal flow or contraflow) can occupy an arc at time t as shown in Eqs. (3.14) and (3.15).

3.4 The Two-Flow EERP Problem

The EERP problem becomes even more challenging when there is more than one type of flow occupy the network simultaneously for unexpected emergency events. In this section, we consider a more realistic case when there are two types of flows that are incompatible (*i.e.*, heterogeneous) and they occur simultaneously. Again, by incompatible, it is meant that the two different types of flow may not occupy a given transportation link or intersection point at the same time. This is quite relevant if safety of evacuees and emergency first responders is a strong concern, which in most cases it is. The first flow is evacuees moving from the hazard area to a safe destination. The second flow is the emergency first responders moving toward the hazard area. Each flow generally traverses the transportation link in the direction opposite of the other. In the two-flow problem, $\mathbf{X}_R \subset \mathbf{N}$ is the set of nodes representing the locations occupied by the first responders. Figure 3.3 shows the bi-directional evacuation network. It is important to note here that we consider the case where there are two roadways between two successive nodes that are opposing in normal flow direction.

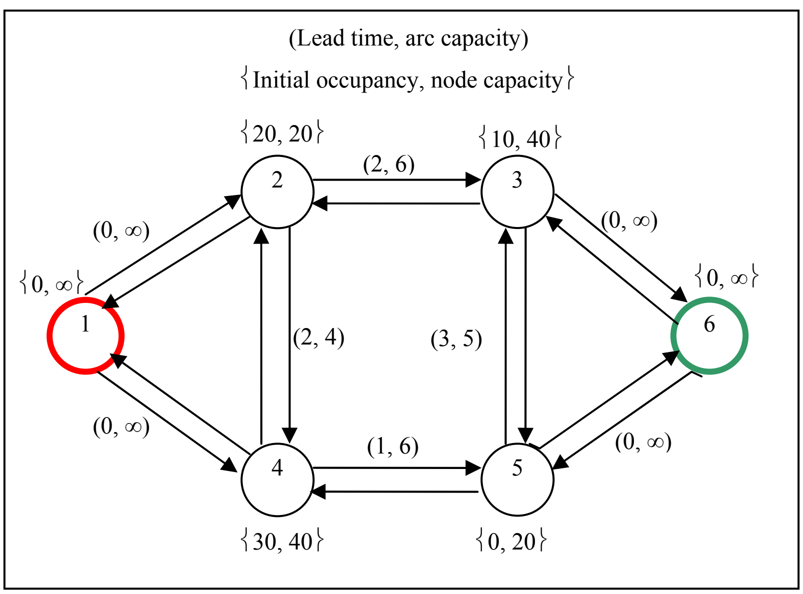


Figure 3.3. Example of two-flow bi-directional evacuation network under normal flow conditions.

3.4.1 Two-Flow EERP Problem with No Contraflow Lane Reversals

This section presents the two-flow EERP model, where there are two opposed, incompatible flows and contraflow lane reversals are not permitted. The evacuee flow moves towards areas of safety and the responder flow moves toward the hazard area.

Problem Parameters:

T : Total number of periods to clear the transportation network

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

p_{k0} : Population of evacuees at node k ($k = 1, \ldots, N$-1) in the network before evacuation begins

w_{k0} : Population of responders at node k ($k = 1, \ldots, N$) in the network before evacuation begins

v_k : Capacity of node k ($k = 1, \ldots, N$) in the network

c_{ij} : Capacity of arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$ where $i \neq j$) in the network

τ_{ij} : Free flow time on arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$ where $i \neq j$) in the network

Primary Decision Variables:

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

$$a_{kt} = \begin{cases} 1, \text{if node } k \text{ is occupied by evacuees during interval } (t, t+\tau_{ik}] \\ 0, \text{otherwise} \end{cases}$$

x_{ijt} : Evacuee flow from node i at beginning of period t (end of period t-1) to node j at end of period t (beginning of t+1)

g_{jit} : Responder normal flow from node j at beginning of period t (end of period t-1) to node i at end of period t (beginning of t+1)

Secondary Decision Variables:

p_{kt} : Population of evacuees at node k (k = 1, …, N-1) in the network at the end of period t

w_{kt} : Population of responders at node k (k = 1, …, N) in the network at the end of period t

O_t^e : Number of evacuees who clear the network at end of period t

O_t^r : Number of responders who clear the network at end of period t

$$\max \quad Z = \sum_{t=1}^{T}(T+1-t)O_t^e + \sum_{t=1}^{T}(T+1-t)O_t^r \tag{3.17}$$

$$\text{s.t.} \quad O_t^e = \sum_{i=1}^{N-1} x_{iNt} \qquad \forall t = 1, \ldots, T \tag{3.18}$$

$$O_t^r = \sum_{i=N}^{2} g_{i1t} \qquad \forall t = 1, \ldots, T \tag{3.18}$$

$$p_{k1} = p_{k0} - \sum_{j=1}^{N} x_{kj1} \qquad \forall k = 1, \ldots, N\text{-}1 \tag{3.19}$$

$$p_{kt} = p_{k(t-1)} - \sum_{j=1}^{N} x_{kjt} + \sum_{i=1}^{N} x_{ik(t-\tau_{ik})} \qquad \forall k = 1, \ldots, N;\ t > 1 \tag{3.20}$$

$$w_{k1} = w_{k0} - \sum_{j=1}^{N} g_{jk1} \qquad \forall k = 1, \ldots, N\text{-}1 \tag{3.21}$$

$$w_{kt} = w_{k(t-1)} - \sum_{j=1}^{N} g_{kjt} + \sum_{i=1}^{N} g_{ik(t-\tau_{ik})} \qquad \forall k = 1, \ldots, N;\ t > 1 \tag{3.22}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} x_{jit} \le c_{ji} e_{jit} \qquad \forall t = 1, \ldots, T;\ i \ne j \tag{3.23}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} g_{ijt} \le c_{ij}\left(1-e_{jit}\right) \qquad \forall t = 1, \ldots, T;\ i \neq j \tag{3.24}$$

$$p_{kt} \le v_k a_{kt} \qquad \forall t = 1, \ldots, T;\ \forall k = 1, \ldots, N \tag{3.25}$$

$$w_{kt} \le v_k(1 - a_{kt}) \qquad \forall t = 1, \ldots, T;\ \forall k = 1, \ldots, N \tag{3.26}$$

The objective function Eq. (3.17) maximizes the number of evacuees and responders exiting the network at each time period t ($t = 1, \ldots, T$) by simultaneously routing the evacuees to their destinations of safety (represented by node N) and responders to their destination (represented by node $N = 1$) early in the time interval 1 to T. The weights are assigned such that it makes it more desirable to route the evacuees to node N and route responders to Node 1 early during evacuation than it is to move them later during the same time interval. Eq. (3.18) sums for each period t the evacuees that reach the destination node N from each node i connected to the destination node using normal flow. In addition, Eq. (3.18) sums for each period t the responders that reach the source node $N = 1$ from each node i connected to the source node using normal flow. Eqs. (3.19) and (3.20) ensure the conservation of evacuee flow for the first and subsequent periods. Eqs. (3.21) and (3.22) are conservation of flow constraints of responder flow for the first and subsequent periods, respectively. Eqs. (3.23) and (3.24) enforce the heterogeneous constraint on the arcs. In other words, an arc (i,j) is used by either responders or evacuees at time t. Eqs. (3.25) and (3.26) are node capacity constraints. These two constraints assure that each node is occupied by either evacuees or responders at each period time.

3.4.2 Two-Flow EERP Problem with Contraflow Lane Reversals

Finally, we consider the EERP problem where contraflow lane reversals are permitted to facilitate both evacuee and responder rapid flow. The two-flow EERP problem with contraflow finds an optimal reconfigured network that maximizes both evacuee and responder flow through the network.

<u>Problem Parameters:</u>

T : Total number of periods to clear the transportation network

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

p_{k0} : Population of evacuees at node k ($k = 1, \ldots, N$-1) in the network before evacuation begins

w_{k0} : Population of responders at node k ($k = 1, \ldots, N$) in the network before evacuation begins

v_k : Capacity of node k ($k = 1, \ldots, N$) in the network

c_{ij} : Capacity of arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$ where $i \neq j$) in the network

τ_{ij} : Free flow time on arc (i,j) ($i = 1, \ldots, N$; $j = 1, \ldots, N$ where $i \neq j$) in the network

<u>Primary Decision Variables:</u>

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

$$r_{jit} = \begin{cases} 1, \text{ if responder normal flow on arc}(j, i) \text{ during interval } (t, t + \tau_{ji}] \\ 0, \text{ otherwise} \end{cases}$$

$$a_{kt} = \begin{cases} 1, \text{ if node } k \text{ is occupied by evacuees during interval } (t, t + \tau_{ik}] \\ 0, \text{ otherwise} \end{cases}$$

x_{ijt} : Evacuee flow from node i at beginning of period t (end of period t-1) to node j at end of period t (beginning of t+1)

y_{ijt} : Evacuee contraflow from node i at beginning of period t (end of period t-1) to node j at end of period t (beginning of t+1), and

g_{jit} : Responder normal flow from node j at beginning of period t (end of period t-1) to node i at end of period t (beginning of t+1)

h_{ijt} : Responder contraflow from node i at beginning of period t (end of period t-1) to node j at end of period t (beginning of t+1)

<u>Secondary Decision Variables:</u>

p_{kt} : Population of evacuees at node k (k = 1, …, N-1) in the network at the end of period t

w_{kt} : Population of responders at node k (k = 1, …, N) in the network at the end of period t

O_t^e : Number of evacuees who clear the network at end of period t

O_t^r : Number of responders who clear the network at end of period t

$$\max \quad Z = \sum_{t=1}^{T}(T+1-t)O_t^e + \sum_{t=1}^{T}(T+1-t)O_t^r \tag{3.27}$$

$$\text{s.t.} \quad O_t^e = \left(\sum_{i=1}^{N-1} x_{iNt} + \sum_{i=1}^{N-1} y_{iNt}\right) \qquad \forall t = 1, \dots, T \tag{3.28}$$

$$O_t^r = \left(\sum_{i=N}^{2} g_{i1t} + \sum_{i=N}^{2} h_{j1t}\right) \qquad \forall t = 1, \dots, T \tag{3.29}$$

$$p_{k1} = p_{k0} - \sum_{j=1}^{N} x_{kj1} + \sum_{j=1}^{N} y_{jk1} \qquad \forall k = 1, \ldots, N\text{-}1 \tag{3.30}$$

$$p_{kt} = p_{k(t-1)} - \sum_{j=1}^{N} x_{kjt} + \sum_{i=1}^{N} x_{ik(t-\tau_{ik})} + \sum_{j=1}^{N} y_{kjt} - \sum_{i=1}^{N} y_{ik(t-\tau_{ki})} \qquad \forall k = 1, \ldots, N;\ t > 1 \tag{3.31}$$

$$w_{k1} = w_{k0} - \sum_{j=1}^{N} \left(g_{kj1} + h_{jk1} \right) \qquad \forall k = 1, \ldots, N\text{-}1 \tag{3.32}$$

$$w_{kt} = w_{k(t-1)} - \sum_{j=1}^{N} g_{kjt} + \sum_{i=1}^{N} g_{ik(t-\tau_{ik})} + \sum_{j=1}^{N} h_{jkt} - \sum_{i=1}^{N} h_{ki(t-\tau_{ki})} \qquad \forall k = 1, \ldots, N\text{-}1;\ t > 1 \tag{3.33}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} x_{jit} \le c_{ji} e_{jit} \qquad \forall t = 1, \ldots, T;\ i \ne j \tag{3.34}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} y_{ijt} \le c_{ij} \left(1 - e_{jit} \right) \qquad \forall t = 1, \ldots, T;\ i \ne j \tag{3.35}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} g_{jit} \le c_{ji} r_{jit} \qquad \forall t = 1, \ldots, T;\ i \ne j \tag{3.36}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} h_{ijt} \le c_{ij} \left(1 - r_{jit} \right) \qquad \forall t = 1, \ldots, T;\ i \ne j \tag{3.37}$$

$$e_{ijt} + r_{ijt} = 1 \qquad \forall t = 1, \ldots, T;\ i = 1, \ldots, N;\ j = 1, \ldots, N;\ i \ne j \tag{3.38}$$

$$p_{kt} \le v_k a_{kt} \qquad \forall t = 1, \ldots, T;\ \forall k = 1, \ldots, N \tag{3.39}$$

$$w_{kt} \le v_k (1 - a_{kt}) \qquad \forall t = 1, \ldots, T;\ \forall k = 1, \ldots, N \tag{3.40}$$

Eq. (3.28) sums for each period t the evacuees that reach the destination node N from each node i connected to the destination node using both normal flow and contraflow. Eq. (3.29) sums for each period t the responders that reach their source node $N = 1$ from each node i connected to the source node using both normal flow and contraflow. Eqs. (3.30)-(3.33) are the conservation of flow constraints for evacuees and responders during the first and subsequent periods, respectively. w_{kt} is the number of responders occupying node k at time t. Eqs. (3.34)-(3.37) ensure that only one type of flow (normal flow or contraflow) occupies an arc at time t. Eq. (3.38) ensures that only one type of flow (evacuee or responder) occupies an arc at time t and Eqs. (3.39) and (3.40) ensure that only one type of flow is at a node at time t. These enforce the incompatibility of flow constraint.

3.5 Computational Experiments – A Case Study

The models presented in Sections 3.3.1, 3.3.2, 3.4.1 and 3.4.2 are applied to an actual real-world dataset. The four proposed models are applied to the dataset used by Shekhar and Kim (2006), which consists of the population surrounding a nuclear power plant in Monticello, Minnesota. The details of the dataset are given in Appendix A. Figure A.1 in Appendix A shows the map of the nuclear power plant in Monticello, Minnesota. The blue path in the map shows the interstate I-94.

The demographic data of the dataset are based on Census 2000 population data. The total number of citizens is 41,950, which is spread throughout the area. In the dataset, there are 47 nodes and 148 travel arcs. Each arc and node has an associated capacity. The set of arcs contain high granularity arcs in that the set of arcs include a high number of interstate highways and arterials. Table A.1 and Table A.2 in Appendix A present roadway (arc) and node data of the Minnesota nuclear power plant. The highlighted cells in Table A.1 denote the arcs connected to the evacuee sink node (Node 47). For this research, the dataset is modified and expanded to include a population of emergency responders that moves toward the hazard area. The total number of responders used in this research is 230 (see Table A.2 in Appendix A). Also, since the objective function is weighted by t (t = 1, …, T), where T is a user predefined desired time to complete the evacuation, T is arbitrarily set to 200 time periods.

3.6 Discussion of Results

Table 3.1 summarizes the characteristics of the ILP formulations of the single-flow with no contraflow, single-flow with contraflow, two-flow with no contraflow, and two-flow with contraflow EERP models. The table shows the total number of integer variables, total variables and constraints for the proposed formulations. Comparing the total number of variables in the single-flow and the two-flow with no contraflow scenarios, the number of variables increased about 56% in the two-flow. Also, by comparing the contraflow scenarios of the single-flow and two-flow, the total variables increased about 68%. LINGO 9.0 optimization software by LINDO Systems, Inc. is used to solve the four EERP ILP models to optimality. In other words, the global optimum is found for each EERP model.

Table 3.1. Summary of number of variables, integers, constraints for the proposed EERP model formulations.

	EERP Model			
Model Characteristic	Single-Flow with No Contraflow	Single-Flow with Contraflow	Two-Flow with No Contraflow	Two-Flow with Contraflow
Number of Integer Variables	0	14,800	15,150	24,010
Total Number of Variables (Real and Integers)	29,400	49,201	52,200	72,172
Number of Constraints	36,452	39,103	96,302	116,905

3.6.1 Network Flow Clearance Performance

Table 3.2 summarizes the evacuation performance results for the four EERP models. The output from the models with no contraflow is the schedule of the evacuee and emergency responder flows during each period of time until the network is cleared. The output from the models with contraflow is not only the schedule of the evacuee and emergency responder flows during each period of time until the network is cleared, but the schedule of the contraflow lane reversal is generated. Evacuee network clearance time in the single-flow with contraflow and the two-flow with contraflow are reduced by 36.5%. In terms of solution time, when one additional flow is added to the single-flow network with no contraflow, the solution time increases nearly 29000% (see Table 3.3). When contraflow lane reversals are allowed in the presence of a single flow type (evacuee), the solution time increases 280000%. Comparing the single-flow model with contraflow to the two-flow model with contraflow, the time to solve the two-flow version increases 86%. Thus, it can be seen that allowing contraflow lane reversals reduces the network clearance time in general.

Table 3.2. Summary of the network clearance start time and network clearance end times.

	EERP Model			
Evacuation Performance Measure	Single-Flow with No Contraflow	Single-Flow with Contraflow	Two-Flow with No Contraflow	Two-Flow with Contraflow
Model Solution Time (hh:mm:ss)	00:00:14	11:03:34	1:07:46	20:35:06
Evacuee Flow				
Clearance Start Time	24	24	24	24
Clearance End Time	137	87	137	87
Emergency Responder Flow				
Clearance Start Time	–	–	27	27
Clearance End Time	–	–	67	67

Table 3.3. Comparison of solution times (in seconds) for the EERP models.

Single-Flow with No Contraflow 14 secs	vs.	Single-Flow with Contraflow 39814 secs	% Increase 284285.71
Single-Flow with No Contraflow 14 secs	vs.	Two-Flow with No Contraflow 4066 secs	% Increase 28942.86
Two-Flow with No Contraflow 4066 secs	vs.	Two-Flow with Contraflow 74106 secs	% Increase 1722.58
Single-Flow with Contraflow 39814 secs	vs.	Two-Flow with Contraflow 74106 secs	% Increase 86.13

Evacuee flow behavior evaluation is conducted in the Hurricane Evacuation Study (HES) program managed by FEMA and the US Army Corps of Engineers. The HES program shows that evacuee network clearance behavior tends to follow an S-shaped curve primarily due to evacuee reaction time to an emergency event and not due to immediate mobilization of the evacuees (US Army Corps of Engineers, 2004). However, in many cases, the cumulative flow follows an S-shape. Figure 3.4 shows the general evacuation behavior of evacuees on the west coast of Florida during Hurricane Charley (US Army Corps of Engineers, 2004). In this research, we show the cumulative number of evacuees clearing the network, as well as the cumulative number of responders clearing the network in the two-flow ILP models (see Figure 3.5 through Figure 3.10). It can be seen that the behavior of both types of flow resembles an S-shape. It is important to note here that the cumulative number of evacuees increases very slowly as time progresses. It increases more rapidly at a linear rate and then levels off to increase at a linear rate. The slope of the straight-line portion of the curve equals to the capacity of the lowest capacity (*i.e.*, bottleneck) arcs. If the arc lead times are stochastic and flow-dependent, then the linear portion of the S-curve would actually appear non-linear.

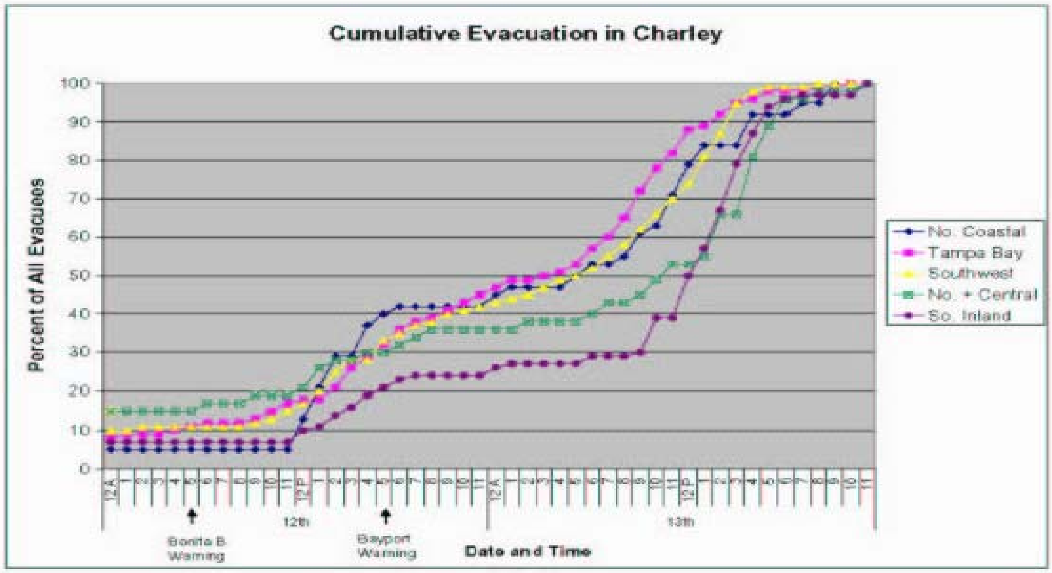


Figure 3.4. Evacuation behavior of Hurricane Charley (used with permission from Mitchell, (2006)).

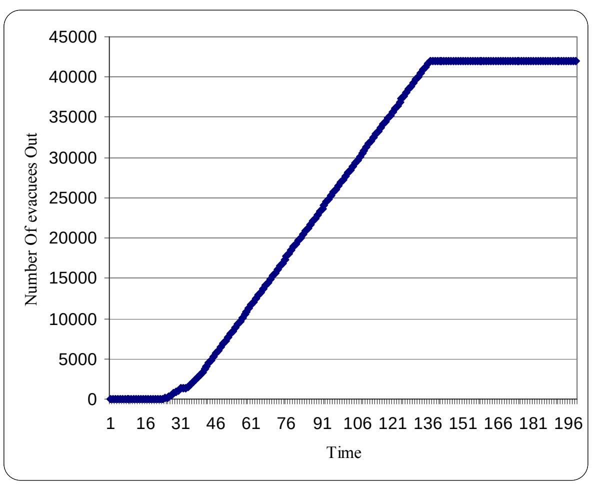


Figure 3.5. Cumulative number of evacuees out for the single-flow EERP model with no contraflow lane reversals.

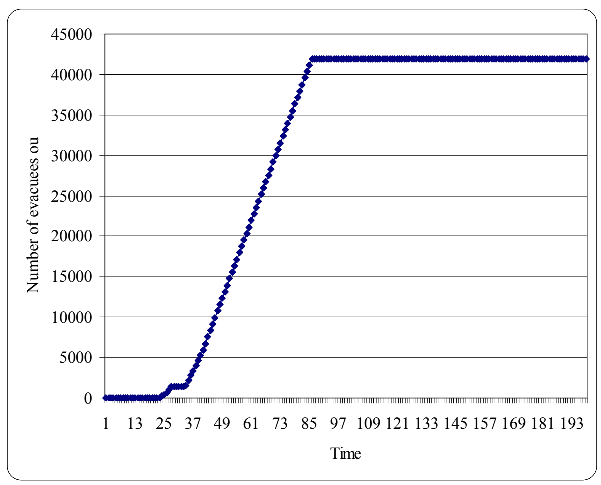


Figure 3.6. Cumulative number of evacuees out for the single-flow EERP model with contraflow lane reversals.

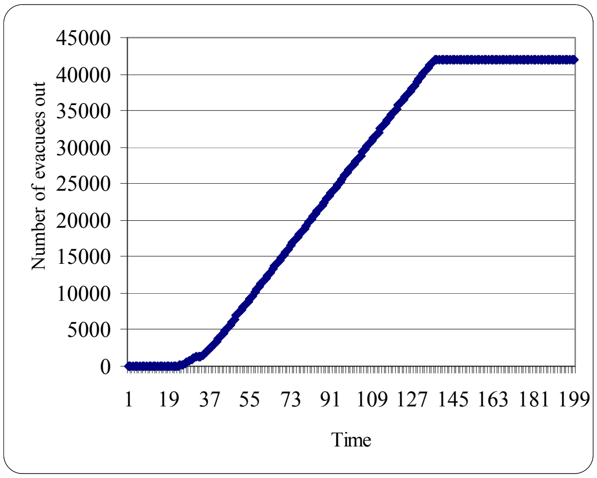


Figure 3.7. Cumulative number of evacuees out for the two-flow EERP model with no contraflow lane reversals.

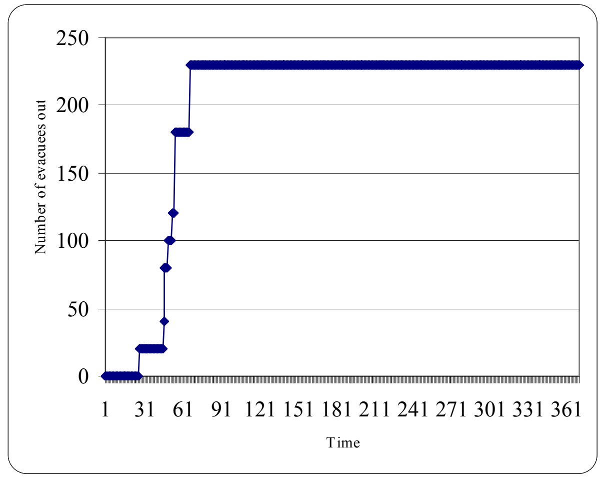


Figure 3.8. Cumulative number of emergency responders in for the two-flow EERP model with no contraflow lane reversals.

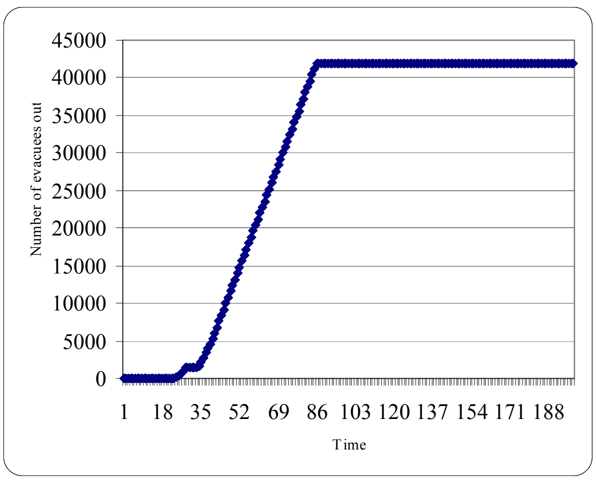


Figure 3.9. Cumulative number of evacuees out for the two-flow EERP model with contraflow lane reversals.

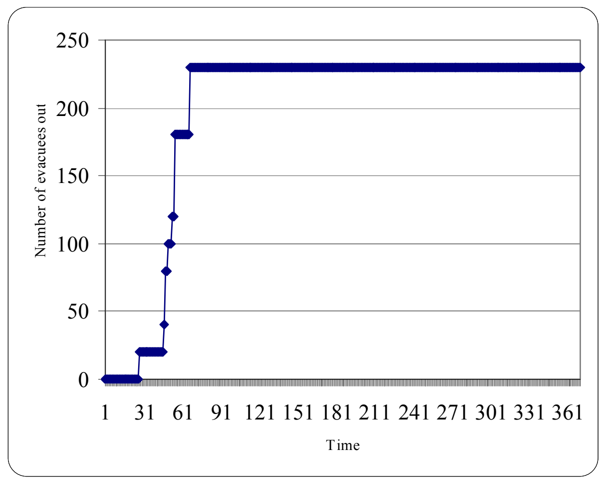


Figure 3.10. Cumulative number of emergency responders in for the two-flow EERP model with contraflow lane reversals.

3.6.2 Utilization of Contraflow Lane Reversals

Another measure of network clearance performance considered in this research is arc usage for normal flow and for contraflow. The number of arcs used for normal flow and the number of arcs used for contraflow for each period t is computed. Arc usage is an important measure of performance for emergency officials, since managing flows during evacuation requires a significant number of emergency and law enforcement personnel (Wolshon *et al.*, 2001), especially in the presence of two incompatible flows. Thus, roadways (arcs) should be utilized in a balanced way between the demand of evacuees and responders. Figure 3.11 through Figure 3.14 show the number of arcs used for normal flow and contraflow at each time *t*.

Figure 3.11 shows the number of normal flow arcs used by evacuees for the single-flow model with no contraflow, and Figure 3.12 shows the number of normal flow arcs and contraflow arcs used by evacuees for the single-flow model with contraflow. Figure 3.11 shows that the peak usage of the normal flow arcs occurs midway during the evacuation. The arc utilization trend behavior shown in Figure 3.12 is noteworthy. It can be seen that, to maximize network flow, contraflow lane reversals are more prominent relative to the number of arcs used for normal flow. This speaks to the impact of contraflow on the objective to maximize flow. Comparing the number of arcs used for normal flow and contraflow in the single-flow EERP model with contraflow to its no contraflow counterpart, the utilization of contraflow arcs is nearly two times the number of normal flow arcs, particularly during the peak evacuation time (see Figure 3.12). This is due to the assumption in Section 3.3, specifically, the assumption where there is no restriction on the number of times contraflow is applied to a single arc.

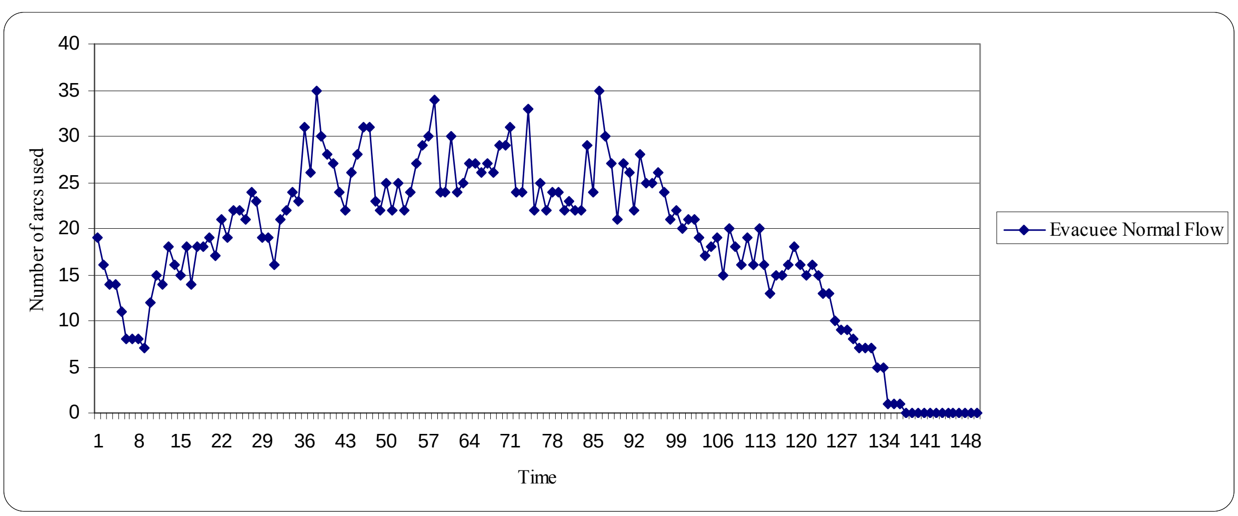


Figure 3.11. Normal flow arc usage by evacuees for the single-flow with no contraflow EERP model.

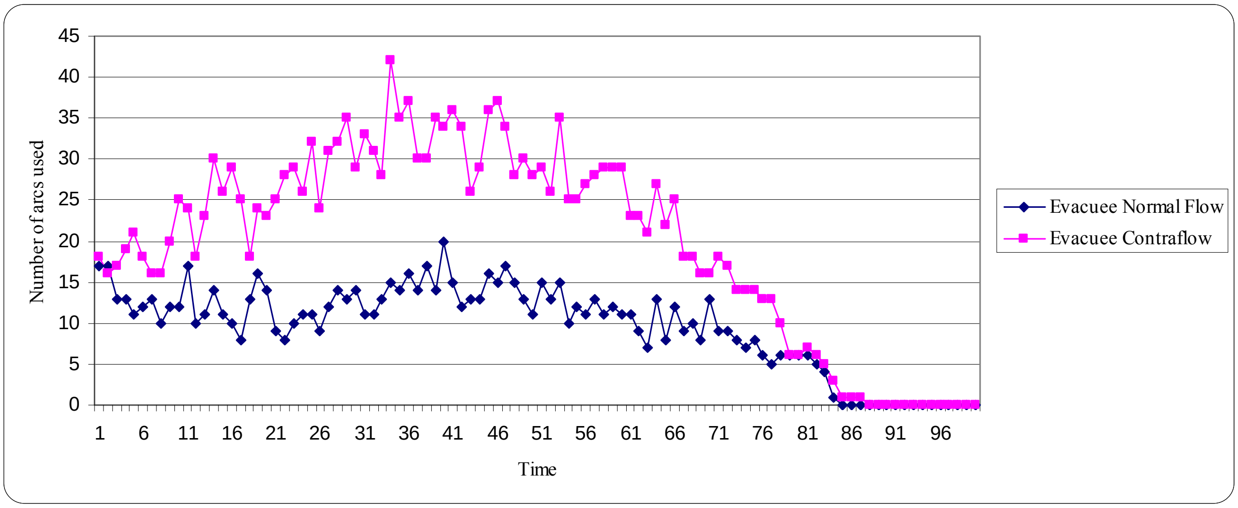


Figure 3.12. Normal flow and contraflow arc usage by evacuees for the single-flow with contraflow EERP model.

It can be seen that arc utilization increases in the scenario where emergency responder flow occurs simultaneously with evacuees (see Figure 3.13 and Figure 3.14). Comparing evacuee flow arc usage in both the single-flow with no contraflow and the two-flow with no contraflow scenario (Figure 3.11 and Figure 3.13, respectively), it is seen that the number of arcs used by normal evacuee flow increased from 35 in the single-flow with no contraflow model to 50 in the two-flow with no contraflow. This is an indication of the impact of the responder flow has on the network arc utilization as the flow occurs simultaneously with evacuee flow. Applying contraflow lane reversals to the two-flow scenario (Figure 3.14) decreases the number of arcs utilized by normal evacuee flow from 50 (seen in Figure 3.13) to 45.

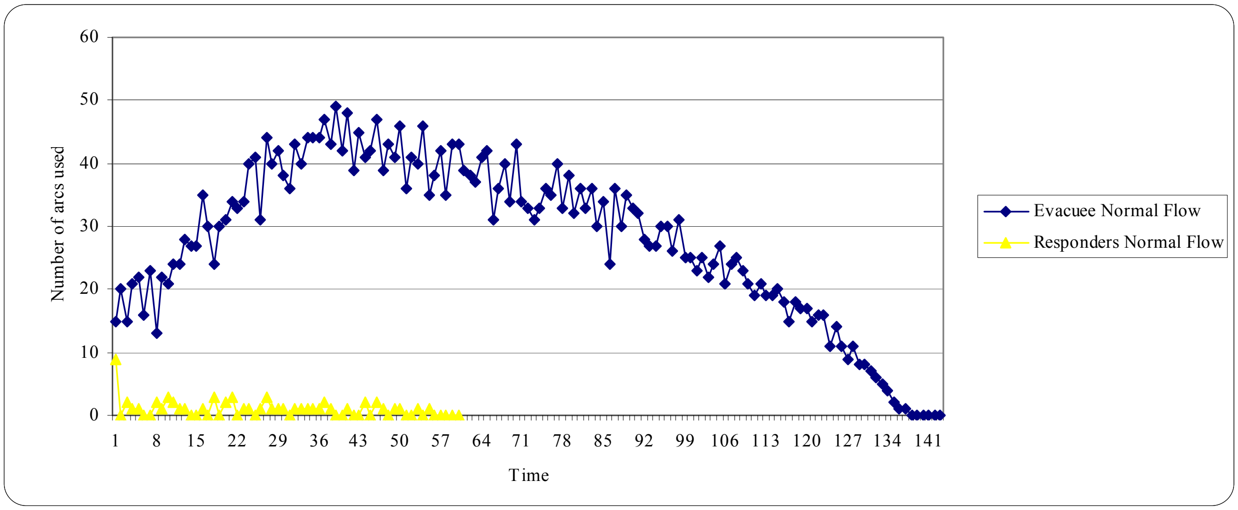


Figure 3.13. Normal flow arc usage by evacuees and emergency responders for the two-flow EERP model with no contraflow.

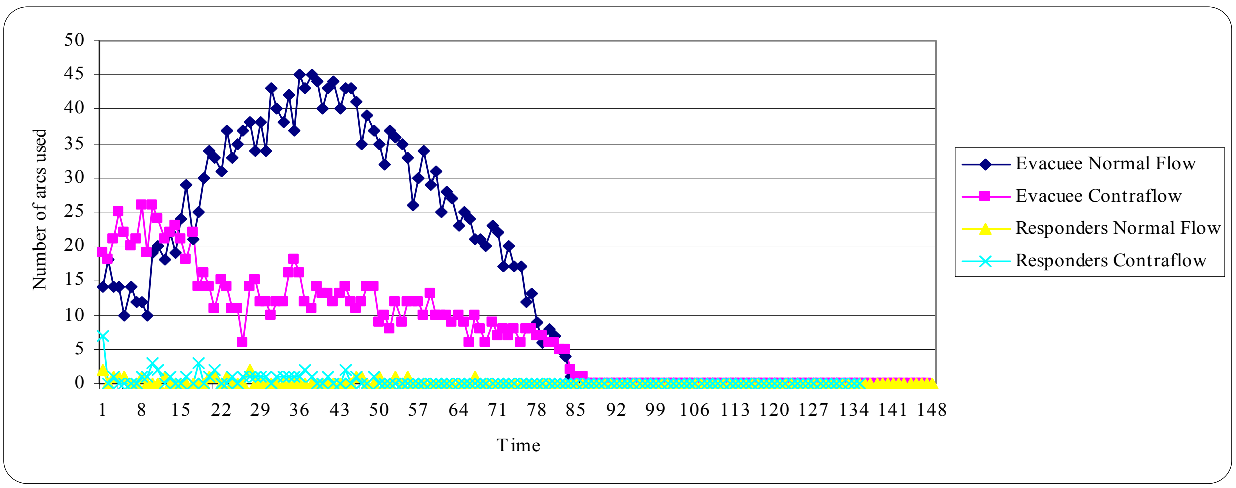


Figure 3.14. Normal flow and contraflow arc usage by evacuees and emergency responders for the two-flow EERP model with contraflow.

3.7 Summary

In this chapter, four integer linear programming models for the EERP problem are presented. Three of these models are new and have not been addressed before in the current literature. These three proposed model formulations lay the foundation for research in an area that has been gaining increasing attention in recent years.

The four models are applied to the dataset used by Shekhar and Kim (2006), which consists of the population surrounding a nuclear power plant in Monticello, Minnesota. The dataset is modified to include an initial population of emergency responders. The individual models are solved optimally using LINGO optimization software. The computational results show that when contraflow lane reversals are allowed, network clearance performance for both the evacuees and the emergency responders improves. In other words, the outflow of evacuees and the inflow of responders are maximized. Thus, evacuation times of evacuees and responders are minimized. However, adding an additional flow and/or allowing contraflow lane reversals increasing the solution time substantially, which is quite undesirable in emergency situations especially in emergencies that are unexpected. Therefore, it is necessary to develop a solution approach that can rapidly generate an evacuation plan for the evacuees and responders and network roadway direction configuration.

CHAPTER 4:
GENETIC-BASED HEURISTIC SOLUTION APPROACH FOR THE EMERGENCY EVACUATION ROUTE PLANNING PROBLEM

4.1 Introduction

The emergency evacuation route planning (EERP) problem with bi-directional flows and contraflow lane reversals is in the class NP due to its combinatorial nature. Finding an optimal solution becomes challenging as the network size (*i.e.*, number of nodes and the number of arcs) increases. Therefore, a heuristic solution approach is needed, especially for EERP problems of realistic size. This chapter proposes a genetic-based heuristic approach for the EERP problem. First, an overview of the class of genetic-based heuristics is given. The objective of the proposed genetic-based heuristic is slightly different than that presented in CHAPTER 3 in that it attempts to maximize the weighted flow for both the evacuees and emergency responders. A detailed description of the proposed genetic-based solution approach using the revised objective is given. Finally, computational results are presented and discussed.

4.2 Overview of Genetic Algorithms

Existing research shows that metaheuristics have been useful in solving combinatorial optimization problems. They are iterative algorithms that start from a complete solution and iteratively modify some of its elements in order to achieve a better solution. There are a number available metaheuristic methods. The most commonly used are genetic algorithms, simulated annealing, tabu search and ant colony optimization. However, each can be modified and hybridized to emulate the others. In this research, a genetic algorithm-based approach is used to solve the EERP problem. It is important to mention here that other metaheuristics can be applied to the EERP problem. However, the main reasons for using a genetic-based solution approach in this study is the wide popularity and acceptance of genetic algorithms and the strength of its parallel search of the solution space.

Genetic algorithms (GAs) are the best known and most widely used representative of the family of evolutionary heuristic search algorithms that attempt to emulate the Darwinian process of natural selection and reproduction, in which the probability of selection for reproduction is directly proportional to their rate of survival in their environment. Holland (1975) develops this class of evolutionary-based procedures in an attempt to formally model and explain adaptation occurring in nature. Goldberg (1989) further explores genetic algorithms and presents a more theoretical framework on which these search procedures are based. Since its introduction, this class of search techniques has been described and analyzed extensively in the literature. Therefore, the conventional genetic algorithm is discussed here, and the reader is referred to the work of Holland (1975) and Goldberg (1989) for a more detailed discussion.

Genetic algorithms, like all other evolutionary-based search algorithms, maintain a population of structures that represent a sample of search points in the space of potential solutions to a given problem. Through its maintenance of multiple solutions, GAs implicitly process, in parallel, a large amount of useful information concerning unseen regions of the solution space. This results in the simultaneous allocation of search effort to many regions at once.

GAs possesses the core algorithmic procedure associated with this family of algorithms: fitness evaluation, selection and reproduction, which involves crossover and mutation genetic-based operations. Figure 4.1 shows the pseudocode for the conventional GA. It is also important to mention that the representation of a solution to any optimization problem is a key issue. If chosen carelessly, the representation scheme can severely limit the manner by which the search views the solution space or the efficiency of the search. Furthermore, the representational scheme determines the feasibility and accuracy of the solution being found.

```
Initialize GA search parameters (P, G, p_c, p_m,)
g := 0
create initial random population of candidate solutions P_g = {s_1^g, s_2^g, s_3^g, ..., s_{P-1}^g, s_P^g}
evaluate(P_g)              // evaluate the fitness (quality) of the candidate solutions
do while (stopping criterion is not met)
{
    g := g +1
    P'_g := select(P_{g-1})      // select solutions for the mating pool
    O_g := crossover(P'_g) // populate set of offspring
    O_g := mutate(O_g)
    P_g ← O_g
    evaluate(P_g)
}end do
```

Figure 4.1. Pseudocode of the conventional genetic algorithm.

4.2.1 Solution Fitness Evaluation

Fitness evaluation is the driving force in simulated evolution in that it is the measurement used to control the selection and reproduction processes of GAs (Goldberg, 1989). The most common approach to measuring solution fitness (quality) is to construct an explicit evaluative procedure, or fitness function $F(s_i)$, where s_i is a solution structure. This function is typically derived from the objective function of the optimization problem, and therefore, tends to be problem-specific. Before the fitness of a solution is determined, it must be decoded so that it has meaning within the problem domain. Each individual solution is then evaluated and assigned a numerical fitness value (or vector of values) as a measure of how well it behaves in the problem domain. The fitness function also provides input to the reproduction mechanism regarding which solutions should have a higher probability of being allowed to reproduce.

4.2.2 Selection

Reproduction begins with the GA selecting candidate solution structures for the mating pool. The structures in the next population are derived from structures selected from the current population. These structures are selected through a stochastic process that chooses a structure s_i according to its fitness $f(s_i)$ relative to the rest of the population. This process influences the progress of the search through the solution space by preferring the more fit structures for reproduction.

A number of different selection schemes have been developed for GAs including tournament selection and rank selection. However, choosing structures according to their proportionality to fitness $\pi(s_i)$, where $\pi(s_i) = f(s_i) \big/ \sum_{j=1}^{P} f(s_j)$ denotes the probability that solution structure s_i is selected for reproduction relative to the population of P structures, is the most commonly used. This selection scheme is called fitness-proportionate selection, which uses a sampling procedure, such as roulette wheel sampling or stochastic universal sampling, to select the members of the mating pool (Holland, 1975).

In order to avoid the search becoming trapped in a particular region of the solution space, structure variation is introduced through stochastic operators that exchange information between individual structures in order to create new structures or to modify existing ones. These are applied to the individuals that are identified as candidates for mating by the selection mechanism. The conventional GA introduces structure variation using crossover and mutation operators (Holland, 1975; Goldberg, 1989). These operators, which mimic the reproduction processes, allow the algorithm to balance exploitation (intensification) and exploration (diversification) of regions in the solution search space (Reeves, 1993). They can also be seen as search operators because they enable the discovery of new solutions in the solution space.

4.2.3 Crossover

Crossover begins by choosing two solutions from the mating pool as “parents” based on the selection mechanism. Once each parent has been identified, a crossover point (or set of crossover points) in each parent is selected at random. The subcomponents of the parent solutions are then exchanged, yielding two new solutions (“children”). These new solutions possess information of each parent and provide new points in the search for further testing. In other words, crossover leads to further exploration within the sub-regions represented by the solutions in the current population (Reeves, 1993). The expectation is that if good subcomponents from two high performing solutions are combined, the children are likely to have equal or improved performance. There is a probability p_c for this operation that determines whether a selected solution undergoes the crossover operation.

4.2.4 Mutation

Holland (1975) introduces mutation as a secondary search operator for the GA. Its purpose is to reintroduce diversity into the population that may have been lost during the search so that it does not converge prematurely to a local optimum. The mutation operation creates random perturbations in the structures in the population. In the conventional GA based on binary vectors, after reproduction, a bit location in the offspring is randomly chosen. The value in that location is arbitrarily complemented, creating a new vector. Mutation is also a probabilistic operator, and the probability p_m of a single mutation is typically very small (Goldberg, 1989). Therefore, each offspring has a relatively low probability of mutation.

4.3 Revised EERP Problem Formulation

Now described is the proposed genetic-based solution approach for the two-flow with contraflow EERP problem. Since this is the problem of greatest interest and the version that is the most complex and the most difficult to solve, the development of the GA-based approach is limited to this specific problem.

First, the objective function used by the GA is discussed. The objective function of the ILP model formulation presented in CHAPTER 3 requires the user to predefine the desired evacuation clearance time *T*. Therefore, the objective function of the genetic-based heuristic is modified, so the predefined time is not necessary. The revised objective is to maximize the weighted flow of both the evacuees and emergency responders, where the weight (volume) on a particular arc is its capacity multiplied by its lead time.

Modeling Assumptions:

- There is one super source node and one super sink node for evacuees;
- There is one super source node and one super sink node for emergency responders;

- 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*;
- The lead time on a given arc τ_{ij} is deterministic and known with certainty;
- The lead time on a given arc is not a function of the number of entities present on that arc;
- There is no limit on the number of arcs in the travel network to which contraflow lane reversals can be applied; and
- The arc flow directions are set at the beginning of the active period of the evacuation and do not change during the period.

4.3.1 Description of the Proposed Genetic-Based EERP Problem Solution Heuristic

To illustrate the implementation of the proposed genetic-based heuristic solution procedure, a simple 10-node, 30-arc lane-based travel network is used. Figure 4.2 shows a 10-node network with 30 arcs, where each arc (i,j) has a capacity and lead time. All node have a capacity, while some of the nodes have an initial population of evacuees and responders. The dashed red arcs indicate those arcs whose flow directions have been reversed to their contraflow directions. Table 4.1 and Table 4.2 summarize the node and arc data associated with the example network presented in Figure 4.2. Nodes 1 and 10 serve as the super source node and the super sink node, respectively, for the evacuees. Nodes 1 and 10 serve as the super sink node and the super source node, respectively, for the responders.

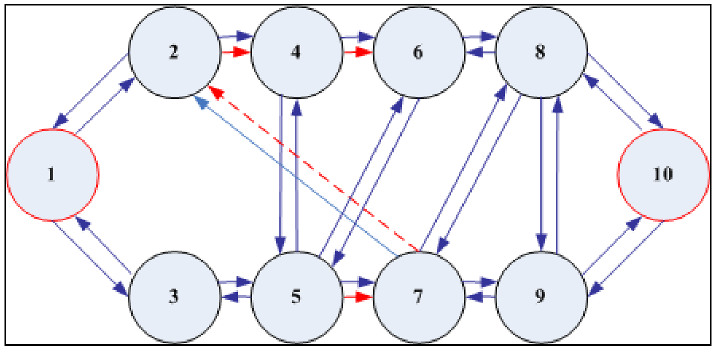


Figure 4.2. Lane-based network example with 10 nodes and 30 arcs.

Table 4.1. Node data for the 10-node, 30-arc lane-based travel network example.

Node ID	Node Capacity	Evacuee Initial Population	Responder Initial Population
1	41950	0	0
2	250	20	0
3	250	20	0
4	250	20	0
5	250	0	0
6	250	0	0
7	250	0	0
8	250	0	0
9	250	0	20
10	41950	0	20

Table 4.2. Arc data for the 10-node, 30-arc lane-based travel network example.

From-Node	To-Node	Arc Capacity	Lead Time	Weight (Arc Cap × Lead Time)	Flow Direction
1	2	41950	0	0	1
2	1	41950	0	0	1
1	3	41950	0	0	1
3	1	41950	0	0	1
2	4	150	9	1350	0
4	2	150	9	1350	1
3	5	250	6	1500	1
5	3	250	6	1500	1
4	5	150	5	750	1
5	4	150	5	750	1
2	7	100	17	1700	0
7	2	150	10	1500	1
5	7	150	10	1500	1
7	5	100	15	1500	0
4	6	100	15	1500	1
6	4	250	11	2750	0
5	6	250	11	2750	1
6	5	200	9	1800	1
6	8	200	9	1800	1
8	6	150	8	1200	1
7	8	150	8	1200	1
8	7	100	7	700	1
7	9	100	7	700	1
9	7	100	7	700	1
8	9	150	17	2550	1
9	8	150	17	2550	1
10	8	41950	0	0	1
8	10	41950	0	0	1
9	10	41950	0	0	1
10	9	41950	0	0	1

4.3.2 EERP Problem GA Solution Representation

The proposed genetic-based heuristic uses a solution representational scheme in which a solution is a binary 0-1 string of fixed length, where the length is the total number of arcs in the network. Figure 4.3 is an example of an individual solution for the 10-node, 30-arc example. The last row is the actual solution representation. A value of 1 indicates the flow on arc (i,j) is in the normal flow direction, and a value of 0 indicates the flow on arc (i,j) is in the contraflow direction.

Arc ID :	1	2	3	4	5	6	7	8	9	10		29	30
From-Node :	1	2	1	3	2	4	3	5	4	5		9	10
To-Node :	2	1	3	1	4	2	5	3	5	4		10	9
Arc Capacity :	41950	41950	41950	41950	150	150	250	250	150	150	…	41950	41950
Lead Time :	0	0	0	0	9	9	6	6	5	5		0	0
Flow Direction :	1	1	1	1	0	1	1	1	1	1		1	1

Figure 4.3. GA solution representational scheme for the EERP problem.

4.3.3 Solution Selection

In the proposed GA solution approach for the EERP problem, fitness-proportionate selection with roulette wheel sampling is used. The individual travel network configurations for the mating pool are selected based on a probability $\pi(s_i)$ that is proportional to their fitness values, *i.e.*, $\pi(s_i) = f(s_i) \big/ \sum_{j=1}^{P} f(s_j)$. Although fitness-proportionate selection is used here, other selection methods can be used, including the more computationally-efficient tournament selection and rank selection. Fitness-proportionate selection is chosen for this research as it exhibits better convergence behavior than tournament selection and rank selection.

4.3.4 Solution Reproduction Operations

Offspring solutions are created using the crossover and mutation genetic operations. In the EERP problem, all produced offspring have the same network specification (*i.e.*, number of nodes and arcs, capacity of the nodes and arcs, and lead time on the arcs). However, the flow directions of the arcs are changed. Implementation of the crossover and mutation operators for the EERP problem is now explained.

4.3.4.1 Crossover

Figure 4.4 illustrate the crossover operation between two individual candidate solution networks, namely Parent 1 and Parent 2, for the EERP problem. A single crossover point in both parents is randomly chosen to be at Arc 10. The new child networks have the same arc flow direction on the first 10 arcs in the data structure. However, the flow directions of the next 20 arcs of the two parents are swapped. The crossover operation for a set of parents occurs at probability p_c.

4.3.4.2 Mutation

In the EERP problem, a candidate solution is mutated by flipping the flow direction for a single arc to its complement with probability p_m. An illustration of the mutation operation is applied to the 10-node, 30-arc example (Figure 4.5). The direction of Arc 7 in the travel network is flipped to its complement, *i.e.*, to the contraflow direction.

Parent 1		Parent 2		Child 1		Child 2	
Arc ID	Flow Direction	Arc ID	Flow Direction	Arc ID	Flow Direction	Arc ID	Flow Direction
1	1	1	1	1	1	1	1
2	1	2	1	2	1	2	1
3	1	3	1	3	1	3	1
4	1	4	1	4	1	4	1
5	1	5	0	5	1	5	0
6	1	6	1	6	1	6	1
7	0	7	1	7	0	7	1
8	1	8	1	8	1	8	1
9	1	9	1	9	1	9	1
10	1	10	1	10	1	10	1
11	1	11	1	11	1	11	1
12	1	12	0	12	0	12	1
13	1	13	1	13	1	13	1
14	1	14	1	14	1	14	1
15	1	15	1	15	1	15	1
16	1	16	1	16	1	16	1
17	1	17	1	17	1	17	1
18	1	18	1	18	1	18	1
19	1	19	0	19	0	19	1
20	1	20	1	20	1	20	1
21	1	21	1	21	1	21	1
22	1	22	1	22	1	22	1
23	1	23	0	23	0	23	1
24	1	24	1	24	1	24	1
25	1	25	1	25	1	25	1
26	1	26	1	26	1	26	1
27	1	27	1	27	1	27	1
28	1	28	1	28	1	28	1
29	1	29	0	29	0	29	1
30	1	30	1	30	1	30	1

Figure 4.4. Illustration of the crossover operation on two individuals for the 10-node, 30-arc network example.

Parent		Child	
Arc ID	Flow Direction	Arc ID	Flow Direction
1	1	1	1
2	1	2	1
3	1	3	1
4	1	4	1
5	0	5	0
6	1	6	1
7	1	7	0
8	1	8	1
9	1	9	1
10	1	10	1
11	1	11	1
12	1	12	1
13	1	13	1
14	1	14	1
15	1	15	1
16	1	16	1
17	1	17	1
18	1	18	1
19	0	19	0
20	1	20	1
21	1	21	1
22	1	22	1
23	0	23	0
24	1	24	1
25	1	25	1
26	1	26	1
27	1	27	1
28	1	28	1
29	0	29	0
30	1	30	1

Figure 4.5. Illustration of the mutation operation on an individual for the 10-node, 30-arc network example.

4.3.5 Fitness Function

Recall that fitness is the driving force in simulated evolution in the genetic algorithm. The breadth-first search (BFS) algorithm is used in the fitness function. BFS is widely used in applications with large-scale graphs (Chow *et al.*, 2005).

4.3.5.1 Breadth-First Search Algorithm

The general BFS is a graph search algorithm that starts at a source node and explores all the neighboring nodes and labels them as explored nodes, so they will not be visited (Hiller and Lieberman, 2001). BFS iteratively searches for a shortest path between all source nodes and the destination of the flow until the best solution is found, at which time the search terminates. It is very similar to other graph search algorithms, like depth-first search and Dijkstra's Algorithm. BFS is simpler than Dijkstra's Algorithm, since it does not need any data structures, which reduces memory consumption. BFS is considered an efficient graph search, since it does not require memory space as other search algorithms do.

The general BFS iterates through a set of stages **S** and a set of levels **L** until all nodes in the set of network nodes **N** are explored. BFS starts at a source node, which is at Level 0. Initially at Stage 0, all nodes in **N** are labeled as unexplored. At Stage 1, all nodes at Level 1 are visited. Then, at each stage $s \in \mathbf{S}$, all nodes are visited at the Level $l \in \mathbf{L}$, where $l = s$. BFS labels each node in **N** by the length of a shortest path (in terms of number of arcs) from the source node. Figure 4.6 is a pseudocode of the general BFS.

```
Procedure: BFS
Input: G(N, A), which is the directed graph G with set
        of nodes N and set of arcs A
Input: Node n, which is the source at which to start the
        search
Initialize: Q = A
Initialize: Q = A
Initialize: Flag for arc (i,j) to 0, ∀arc (i,j) ∈ A        // Flag for arc (i,j) = 0: unvisited
                                                           // Flag for arc (i,j) = 1: visited
                                                           // Flag for arc (i,j) = 2: explored
do while (all arcs in Q are not explored)
{
    for each node i in the unexplored arc (i,j) in Q      ∀arc (i,j) ∈ A, ∀i ∈ N
    {
        if neighboring node j is unexplored                ∀j ∈ N, i ≠ j
        {
            Update Flag for arc (i,j) = 1
            Insert arc(i,j) into Q
            Update Flag for arc (i,j) = 2
        }end if
    }end for
}end do
```

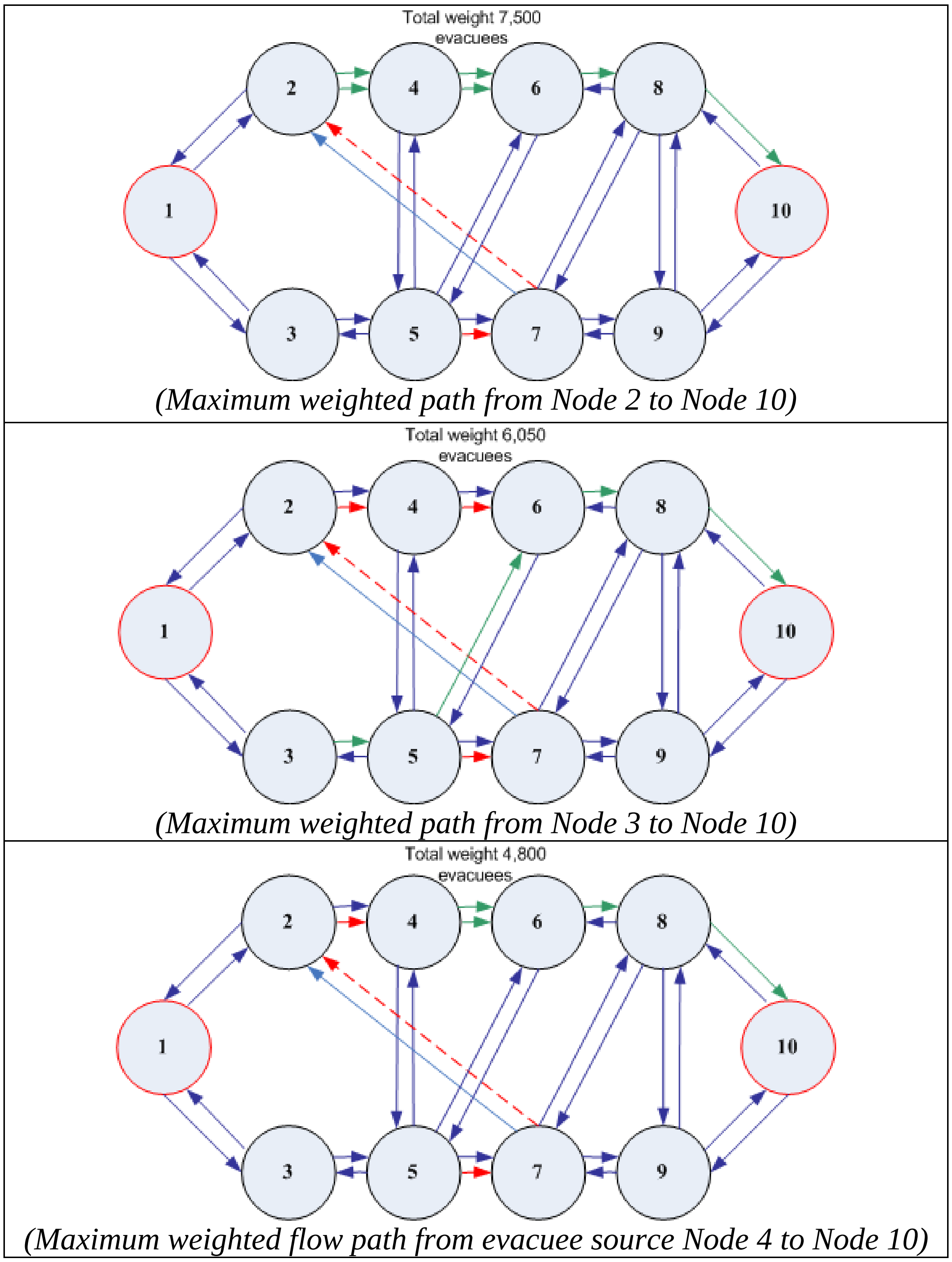
Figure 4.6. Pseudocode of general breadth-first search algorithm.

The general BFS is modified for the fitness function for the proposed EERP problem GA-based solution approach. Firstly, recall that the objective of the EERP problem is to maximize the weighted flow of the evacuees and the responders and that a travel network for the EERP problem can have multiple source nodes. The BFS is modified so it iterates over the number of source nodes in **N** that are initially occupied by evacuees and/or emergency responders. Secondly, the general BFS algorithm searches for the neighboring nodes to find the shortest path in terms of the number of visited nodes. For the EERP problem, the decision to explore a node is based on arc capacity and lead time of the arcs that terminate at that node. Similar to the ILP formulations, the modified BFS does not violate the arc capacity constraints and the arc heterogeneity constraints when searching the neighboring nodes. The output of the modified BFS is a (weighted) route for both evacuees and emergency responders. Figure 4.7 is a pseudocode of the BFS-based fitness function (referred to as M-BFS) for the genetic-based EERP problem solution approach.

```
Input:  G(N, A): directed graph G with set of nodes N and set
          of arcs A
Each node i ∈ N has these properties:
     Initial occupancy  p_i0
     Node capacity       v_i
Each arc (i,j) has these attributes:                          arc (i,j) ∈ A
     Arc capacity        c_ij
     Arc weight          w_ij
     Arc lead time       τ_ij
These arc (i,j) variables are updated iteratively:            arc (i,j) ∈ A
     Evacuee flow        x_ij
     Responder flow      y_ij
     Total flow time     t_ij
do while (any evacuee or responder source node i is occupied)
{
     BFS(source node i)
     Find the Maximum w_ij for all adjacent nodes to node i
     Update flow time t_ij each time an arc (i,j) is explored
     Update Overall Maximum weight for x_ij
}end do while
```

Figure 4.7. Pseudocode of the BFS-based fitness function (or M-BFS).

Using the network node and arc data in the 10-node, 30-arc example network, M-BFS is run, and the maximum weighted flow paths from Node 4 to Node 10 are shown in Figure 4.8 and Figure 4.9. Figure 4.8 shows the paths for the evacuees. Since evacuees initially occupy three nodes, M-BFS is executed three times, once from the different source Nodes 2, 3 and 4. The green routes indicate the maximum weighted flow paths of evacuees. Figure 4.9 shows the paths for the responders, respectively. The red dashed arcs in each figure represent contraflow directions.



(Maximum weighted path from Node 2 to Node 10)

(Maximum weighted path from Node 3 to Node 10)

(Maximum weighted flow path from evacuee source Node 4 to Node 10)

Figure 4.8. Maximum weighted flow paths from all source nodes initially occupied by evacuees.

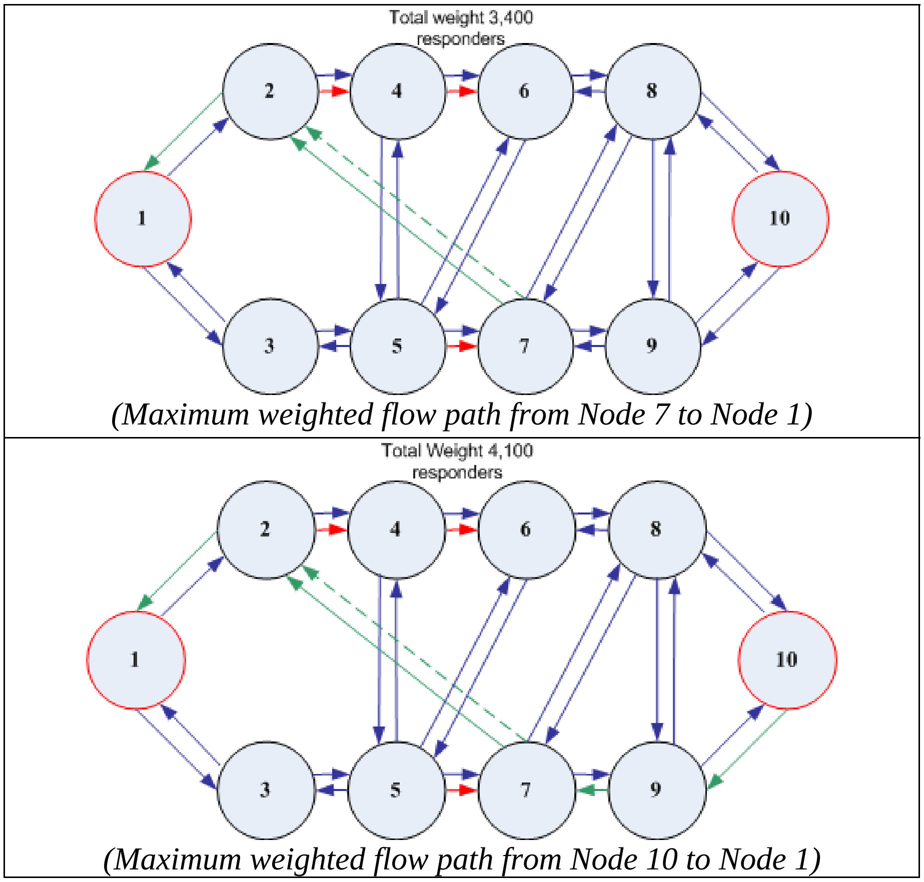


Figure 4.9. Maximum weighted flow paths from all source nodes initially occupied by responders.

4.4 <u>Computational Experiments and Analysis</u>

The genetic-based solution procedure for the EERP problem is implemented in the C programming language. It is coded specifically for the two-flow with contraflow EERP problem. Similar to the proposed ILP formulations, the GA-based solution approach is applied to the dataset of Shekhar and Kim (2006).

4.4.1 GA Parameter Tuning

Before applying the proposed GA-based solution heuristic to the two-flow with contraflow EERP problem, it is important to set the GA search control parameters (population size P, number of generations G, probability of crossover p_c, and probability of mutation p_m) as the values of these are problem-dependent. Therefore, an empirical study in which the parameter values are varied is conducted. Table 4.3 summarizes the range of values for each parameter. The size of population P is set to 100 and 200, and, for each population level, the number of generations G is set to 200, 500 and 1000. The probability of crossover is set to 85%, 90% and 95%, and the probability of mutation is set to 1%, 3% and 5%. Note that the GA-based solution procedure is run for R = 30 replications, which is arbitrarily chosen. For each replication, the search is run from a different initial population of network configurations in the search space. This multi-start search approach is used to develop insight into the inherent variability of the solution procedure due to its randomized nature.

Table 4.3. Range of GA search control parameter values used for parameter tuning.

GA Search Control Parameter	Range of Values
Population Size, P	[100, 200]
Number of Generations, G	[200, 500, 1000]
Probability of Crossover, p_c	[85%, 90%, 95%]
Probability of Mutation, p_m	[1%, 3%, 5%]
Number of Random Replications, R	30

Figure 4.10 shows the convergence behavior of the GA-based solution procedure for one representative replication (Rep 30) of the 30 replications for the parameter setting P = 200, G = 500, p_c = 90% and p_m = 1%. The Avg Obj Val is the average objective function value (*i.e.*, fitness) of the population at each generation. The Max Obj Val is the single best (largest since

we are maximizing) objective function value that occurs in each population at each generation. The Best Obj Val is the overall best objective function value found since the start of the replication. This value is updated during a generation only when a better value is found. The final value is reported at the end of the replication. Figure 4.10 shows that improvement in average performance from generation to generation is steady, although not perfectly monotonic. After the first few generations (about Generation 15), there seems to be no great leaps in improvement, demonstrating that the GA exhibits behavior characteristic of this class of search heuristics. Notice that the search seems to converge well before Generation 500. Therefore, the solution time for a single replication can be reduced considerably if the search is stopped before Generation 500, which is reasonable. However, to allow for adequate time for the search to converge when the crossover and mutation probabilities are varied, P = 200 and G = 500 are used and fixed for the different combinations of probabilities. Therefore, the total number of solution evaluations per random replication is 100,000.

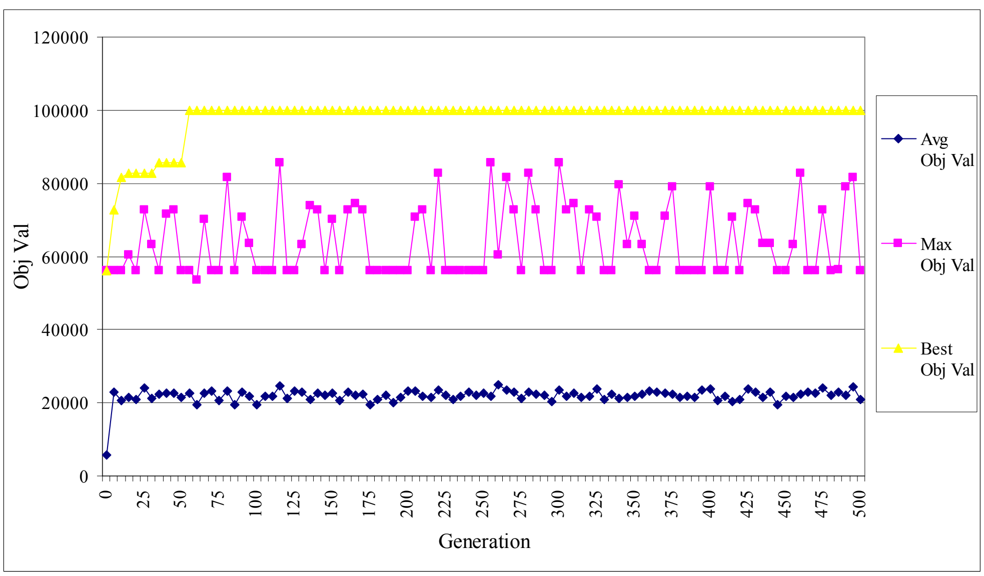


Figure 4.10. Average, maximum and overall best fitness values with GA parameters P = 200, G = 500, p_c = 90% and p_m = 1% for Replication 30.

Table 4.4 summarizes the heuristic performance for each crossover and mutation probability combination at P = 200 and G = 500 for the two-flow with contraflow EERP problem. Column 3 (Max Overall Best Obj Val) is the single maximum overall best objective function value over all 30 replications. Column 4 (Avg Overall Best Obj Val) is the average of the overall best objective function values over all 30 replications. Column 5 (Std Dev) is the standard deviation of the overall best objective function values over all 30 replications. Column 6 (95% CI Half-Width) is the half width of the 95% confidence interval of the overall best objective function values over all 30 replications. Although there is no statistical difference in the means across the different settings, the half-width, which uses the corresponding value in Column 5, gives an indication of the consistency of the proposed algorithm in finding a good solution. Figure 4.11 through Figure 4.16 show the performance trends graphically as the crossover and mutation probabilities are varied.

Table 4.4. Summary of the GA-based solution procedure for various GA search parameter value.

p_c	p_m	Max Overall Best Obj Val (Over 30 Reps)	Avg Overall Best Obj Val (Over 30 Reps)	Std Dev	95% CI Half-Width
85%	**1%**	97,450	85,685.00	6,210.31	2,222.29
85%	**3%**	98,650	85,145.00	6,475.27	2,317.10
85%	**5%**	96,650	82,148.00	11,688.28	4,182.52
90%	**1%**	99,950	85,358.33	6,692.01	2,394.66
90%	**3%**	95,600	81,168.33	9,736.20	3,483.99
90%	**5%**	94,600	85,691.67	5,383.57	1,926.45
95%	**1%**	97,450	84,368.33	5,690.93	2,036.43
95%	**3%**	94,400	86,710.00	6,580.08	2,354.61
95%	**5%**	97,150	84,575.00	8,535.81	3,054.45

Figure 4.11 shows that, in general, as the probability of mutation p_m decreases and as probability of crossover p_c increases, the more consistent the GA-based solution approach is in finding a high-quality overall best solution. In other words, the 95% confident interval half-width decreases as p_c increases and p_m decreases. Figure 4.12 and Figure 4.13 seem to suggest that when both p_c and p_m are set to medium to low values, the heuristic performance is generally good in terms of the maximum overall best objective and the average overall best objective.

Based on this empirical study, the best values for the crossover and mutation probabilities are not clear due to the conflicting trends. Therefore, an average ranking position approach is used to select the “best” settings. Table 4.5 summarizes the rank positions of heuristic performance of the different p_c and p_m settings in terms of the Max Overall Best Obj Val, the Avg Overall Best Obj Val and the 95% CI Half-Width. The settings are sorted in ascending order of average rank position. Based on the average rank position, p_c = 85% and p_m = 1% are selected for this EERP problem. An appropriate selection of parameter settings for any GA-based solution procedure could significantly improve the performance of the search. As the primary intent of this research is to propose an approach to solve the EERP problem, the attempt to determine more appropriate (and perhaps more robust) parameter settings is left for future study. The final set of parameter values that enable the GA-based solution heuristic to exhibit the desired convergence behavior is listed in Table 4.6.

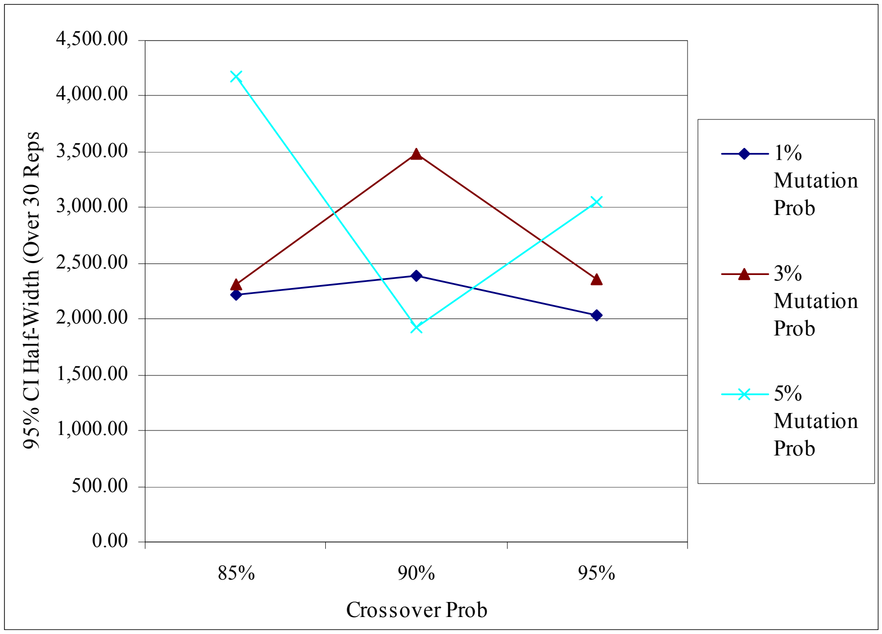


Figure 4.11. Crossover probability vs. 95% confidence interval of the overall best objective function values.

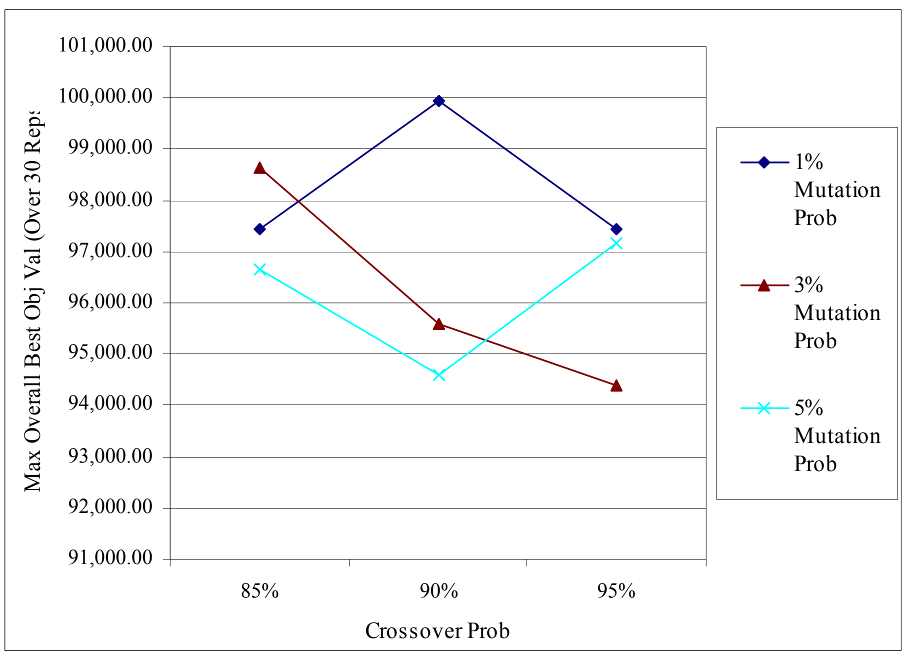


Figure 4.12. Crossover probability vs. maximum of the overall best objective function values.

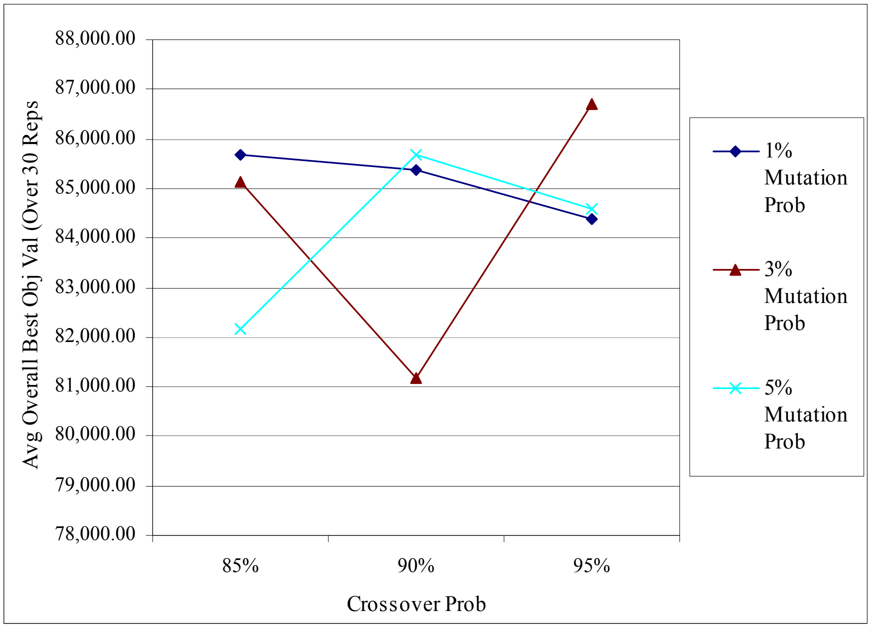


Figure 4.13. Crossover probability vs. average overall best objective function values.

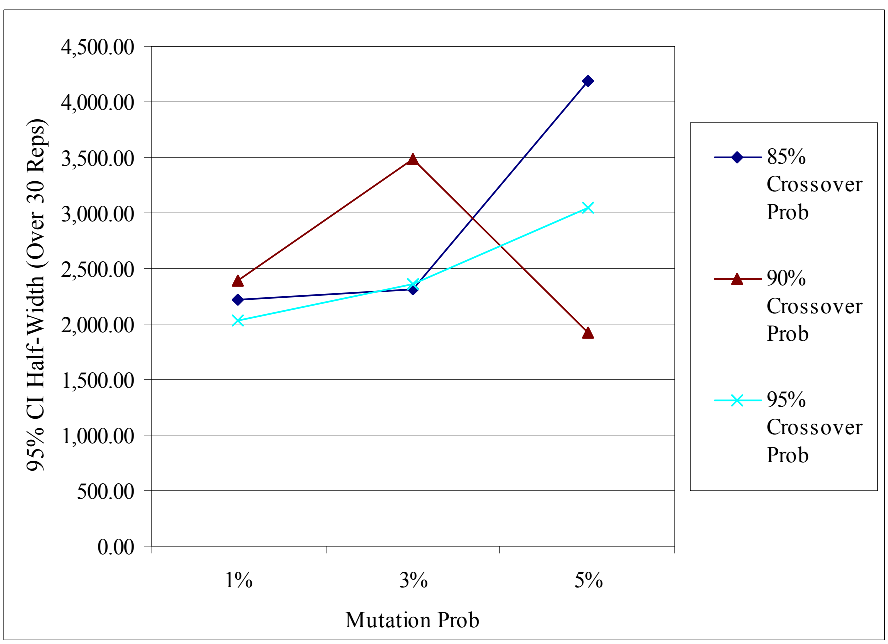


Figure 4.14. Mutation probability vs. 95% confidence interval of the overall best objective function values.

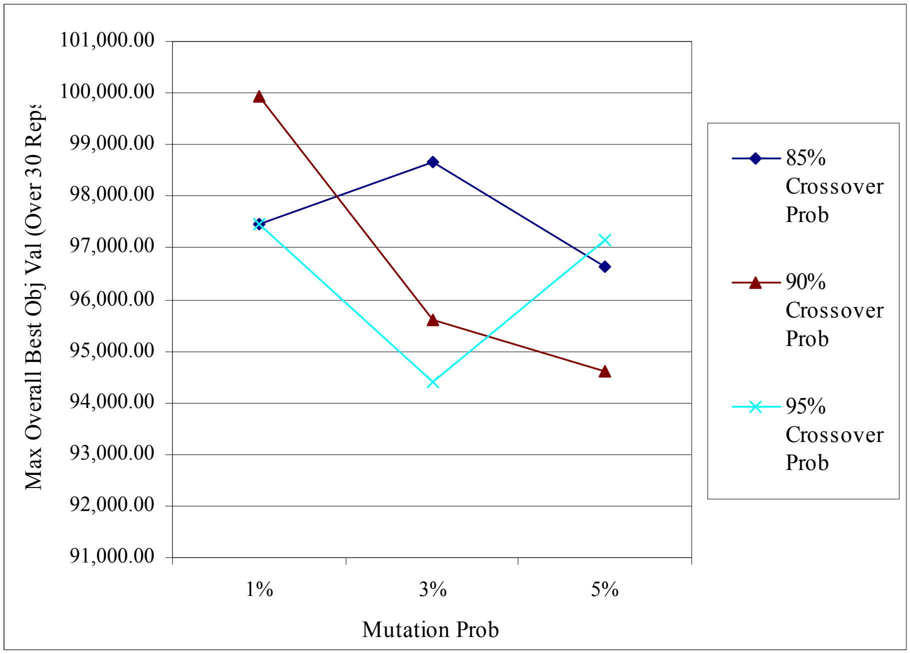


Figure 4.15. Mutation probability vs. maximum of the overall best objective function value.

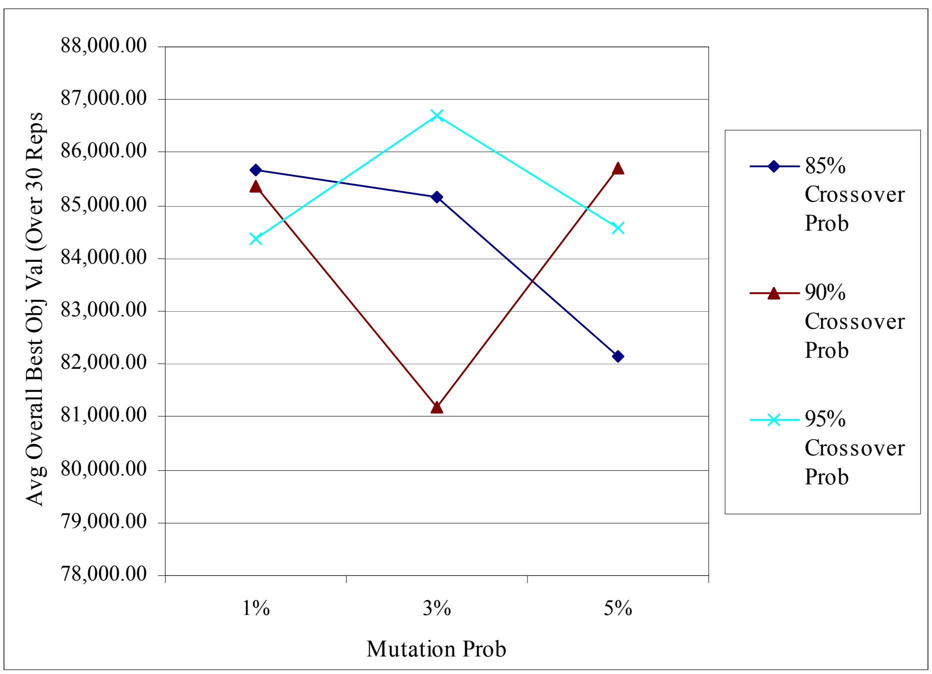


Figure 4.16. Mutation probability vs. average of the overall best objective function values.

Table 4.5. Rank positions of the crossover p_c and mutation p_m parameter settings according to the max overall objective value, avg overall objective value and the 95% confidence interval half-width.

		Rank			
p_c	p_m	Max Overall Best Obj Val	Avg Overall Best Obj Val	95% CI Half-Width	**Average Rank**
85%	**1%**	3	3	3	3.000
85%	**3%**	2	5	4	3.667
90%	**1%**	1	4	6	3.667
90%	**5%**	8	2	1	3.667
95%	**1%**	4	7	2	4.333
95%	**3%**	9	1	5	5.000
95%	**5%**	5	6	7	6.000
85%	**5%**	6	8	9	7.667
90%	**3%**	7	9	8	8.000

Table 4.6. Final genetic algorithm search control parameter settings.

GA Search Control Parameter	**Value**
Population Size, P	200
Number of Generations, G	500
Probability of Crossover, p_c	85%
Probability of Mutation, p_m	1%
Number of Random Replications, R	30

4.5 Discussion of Results

A dual processor personal computer with 2.8 GHz CPU, and 1.0 GB RAM is used to run the proposed GA-based solution heuristic. The GA is run for 30 replications requiring an average of 21.6 hours CPU time to complete the 30 replications, which is 0.72 hours (or, 43.2 minutes) per replication. Across the 30 replications at the parameter settings in Table 4.6, Replication 13 produced the maximum overall best objective function value. Table B.1 in the Appendix section shows the best network configuration generated by the GA-based heuristic approach, including the arcs that are used for normal flow and those that are used for contraflow. The network clearance time performance of the best obtained network configuration is observed. Evacuees need 102 time periods, and the emergency responders need 84 time periods to clear the network to get to their destinations. Evacuee and responder clearing time of the best network configuration obtained from the GA heuristic approach degrade17.2% and 25.4%, respectively, from the ILP optimal solutions.

4.6 Summary

A genetic-based solution approach is used to find a high quality solution for the EERP problem. First, the problem formulation is revised, where the objective of the GA is to maximize the weighted flow for both evacuees and responders. The problem is revised so there is no need to provide a predefined desired network clearance time *T*, as in the objective of the proposed ILP model formulations in CHAPTER 3. Although the objectives of both the ILP formulation and GA-based heuristic solution procedure are different, both provide emergency officials with a reasonable emergency evacuation routing plan for both evacuees and emergency first responders.

A major advantage of using the proposed GA-based procedure is the solution time, which is reduced dramatically relative to the ILP formulation for the two-flow with contraflow problem proposed in CHAPTER 3. Although the total solution times are similar in this study, the run time for the GA-based heuristic approach is a function of the number of solution evaluations (*i.e.*, the number of individuals evaluated during a single replication) and the number of random replications, which is arbitrarily set. If the number of generations is reduced and/or the number of replications is reduced, then a significant time savings would be realized.

CHAPTER 5:
SUMMARY OF RESEARCH AND PLANS FOR FUTURE WORK

5.1 Summary of the Research

The continual growth of population and the frequency of natural, man-made and technological disasters stimulate a need for efficient and reliable emergency evacuation route planning (EERP) procedures to minimize human loss and property damage. This research addresses the EERP problem from a perspective never before considered formally in research and, more importantly, in practice. This perspective is to simultaneously consider two incompatible and traditionally opposed flows. The primary contribution of this research is that it serves as the initial efforts to formulate and solve this practical problem.

CHAPTER 2 summarizes the current research literature that addresses the emergency evacuation routing problem. This problem has been addressed from using analytical mathematical programming models, queuing models and simulation models. The existing 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-world emergencies, heterogeneous, incompatible flows often occur simultaneously, especially in unanticipated emergencies. By incompatible, it is meant that the two different flows cannot occupy a given lane and merge or crossing point at the same time. In addition, contraflow lane reversals have been considered only in the presence of one type of flow. In essence, a review of the literature reveals that the existing analytical, queuing and simulation models do not consider simultaneous, opposing heterogeneous network flows with contraflow lane reversals.

In CHAPTER 3, four integer linear programming model formulations for the EERP problem are presented. Three of these models have not been formulated before in the current literature. These three model formulations lay the foundation for research in an area that has been gaining increasing attention in recent years. Specifically, the models, which consider simultaneous, opposing heterogeneous network flows and contraflow lane reversals, are a primary contribution of this research. The three models are presented in a incremental fashion. The first model is an extension of the single-flow model, where, considering only the single flow of evacuees moving from the hazard area to areas of safety, contraflow lane reversals are permitted. Second, the flow of emergency responders moving towards the hazard area is considered simultaneously with the opposed flow of evacuees with no contraflow lane reversals. The third is an ILP model that considers both the evacuee and responder flows and contraflow lane reversals are allowed. All four EERP model formulations are solved to optimality using real-world population and travel network data. The data are from the population and travel network surrounding the nuclear power plant in Monticello, Minnesota. The output from each model is the time schedule at which evacuee and responder flow will use contraflow to clear the network. From the computational results from solving all four EERP models using the Minnesota nuclear power plant dataset, evacuee and emergency responder flow are both maximized by utilizing contraflow lane reversals. Thus, evacuation times of evacuees and responders are minimized.

An observation when solving the three proposed problems is the time required to solve the problems. The time to solve the problems increases exponentially as the problem grows in size (*i.e.*, in the number of nodes and in the number of arcs) and complexity. The time required to solve the two-flow problem with contraflow is over 20 hours, which is unreasonable, especially in an emergency situation. This motivates the need to develop intelligent heuristic solution approaches that generate high-quality solutions quickly.

CHAPTER 4 presents a proposed genetic-based heuristic approach for the EERP. The objective function is revised so the predefined evacuation time limit T (required by the proposed ILP model formulations) is not required. After a revised objective which is to maximize the weighted evacuee and responder flow, where the weighted flow for each is computed as the capacity of an arc multiplied by that arc's lead time.

An important component of any genetic-based procedure is the fitness function. The fitness function for the GA-based heuristic solution procedure for the EERP problem evaluates the objective of each route found from all occupied nodes in the network, so the routing with the maximum weighted flow is obtained. The fitness function uses a modified version of the breadth first search (BFS) algorithm. Similar to the ILP formulations, the genetic-based heuristic solution procedure is applied to the Minnesota nuclear power plant dataset. After tuning the GA search control parameters by conducting an intensive pilot study that varied the GA search parameters, the proposed EERP heuristic solution procedure identifies a network configuration that attempts to maximize the weighted flow of evacuees and responders.

Applying the genetic-based heuristic solution procedure to the Minnesota nuclear power plant dataset and solving the two-flow problem with contraflow problem, the solution time is reduced dramatically. The GA generates an evacuation network configuration with contraflow solution in 43.2 minutes per replication compared to the required solution time for the ILP formulation of the same problem, which is just under 21 hours. Although the total solution times are similar in this study, the run time for the GA-based heuristic approach is greatly influenced by the number of solution evaluations and the number of random replications. If the number of solution evaluations and/or the number of replications is reduced, then a significant amount of solution time would be saved.

5.2 Future Work

This research investigates the emergency evacuation route planning problem and proposes two modeling and solution approaches – ILP and genetic-based heuristics – to solve this problem. We are confident that the research presented in this dissertation and the conclusions drawn has laid a sufficient foundation for several areas of further study.

One area that needs additional study is incorporating flow-dependent roadway travel times in the evacuation route planning decisions. In this research, it is assumed that roadway travel times are independent of the amount of flow on the roadway during a given time. However, from queueing theory, it is well-known that, as the number of entities increase within a network, the average time per entity spent in the network increases, often quickly and dramatically, due to the increased congestion. A worthwhile study would be to consider arc lead times a function of the number of evacuees and/or responders on the arc at a given time.

Another area of further study is to consider different levels of awareness of the people during evacuation. People have different level of awareness about what is happening during an emergency. A high percentage of people will not respond immediately to an emergency when a hazardous event takes place, and will not egress immediately (Lee *et al.*, 2004). There are three time periods that should be considered:

(1) The period between the time at which the emergency incident occurs and the time at which a person becomes aware of the incident;

(2) The period between the time at which it is decided by a person to start egress motion and the time at which an egress path is chosen and taken; and

(3) The period between the time at which a person chooses and takes an egress path and the time at which the person clears the network.

In modeling EERP, these time periods could be incorporated as they take place in real-life emergency incidents.

Another area that needs additional study is controlling traffic flow under contraflow lane reversals. Applying contraflow lane reversals is an intensive task on enforcement officials as they need to manually direct traffic during a lane reversal. Officials block each entrance ramp of the same direction of the traffic and each exit ramp is temporarily converted to an entrance ramp (Wolshon *et al*., 2001). Controlling traffic in such ways require time and numerous numbers of officials. Although, in the developed GA, contraflow is not applied more than once, the proposed ILP model formulations could still have an additional constraint that controls the maximum number of times an arc is reversed.

Lastly, the application of the three proposed ILP model formulations and the GA-based heuristic approach for the EERP problem to different geographical datasets, such as coastal areas and metropolitan areas, should be performed. This will allow the study of the influence of the characteristics of different geographical regions on the ILP and GA solution approaches.

APPENDIX A:
MONTICELLO, MINNESOTA NUCLEAR POWER PLANT DATASET

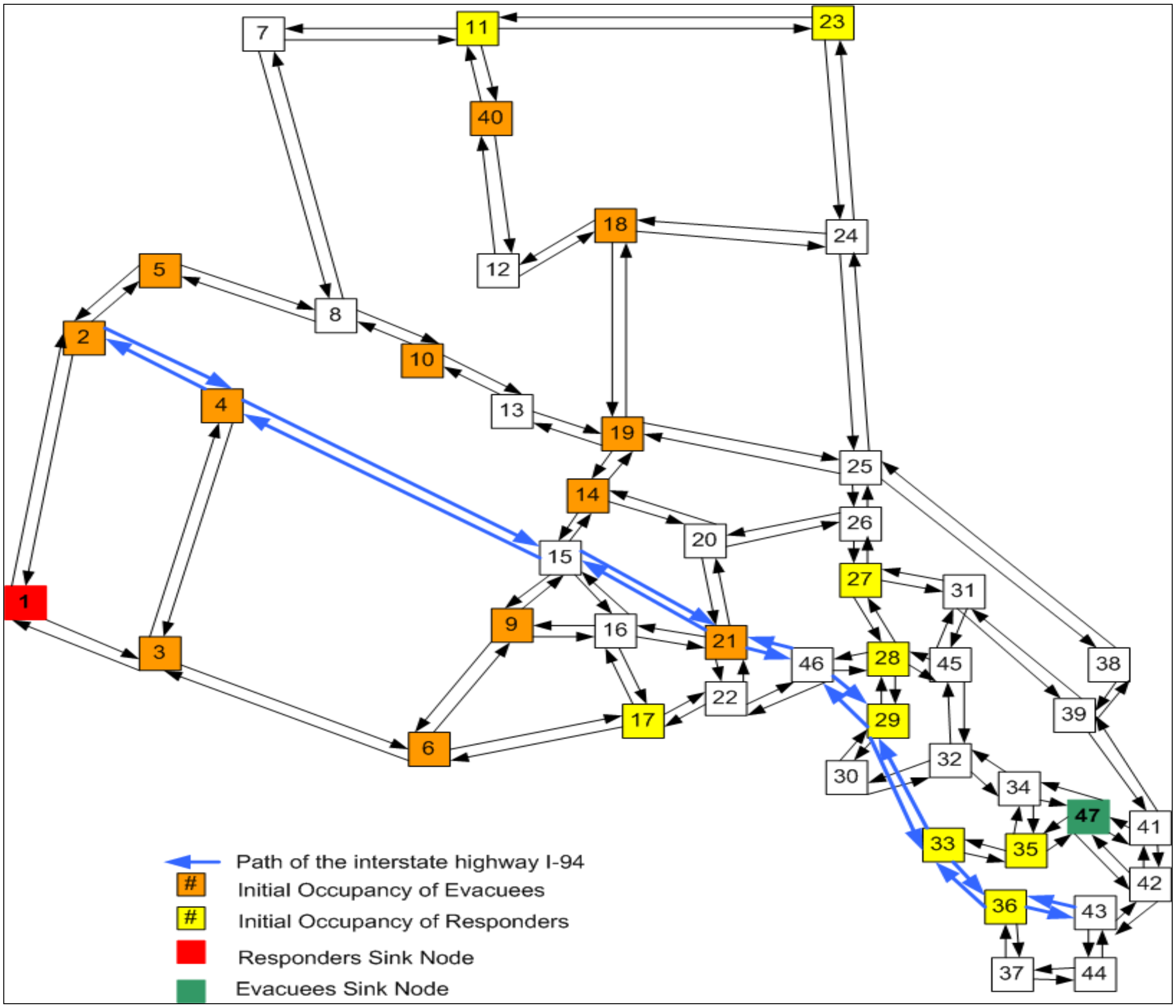


Figure A.1. Map of the highways and arterials around nuclear power plant in Monticello, Minnesota.

Table A.1. Arc data of the Monticello, Minnesota nuclear power plant.

From Node	To Node	Arc Capacity	Lead Time
1	2	150	18
2	1	150	18
1	3	150	9
3	1	150	9
2	4	250	6
4	2	250	6
2	5	150	5
5	2	150	5
3	4	100	17
4	3	100	17
3	6	150	10
6	3	150	10
3	9	100	15
9	3	100	15
4	15	250	11
15	4	250	11
5	8	200	9
8	5	200	9
6	9	150	8
9	6	150	8
6	17	100	7
17	6	100	7
7	8	150	17
8	7	150	17
7	11	150	6
11	7	150	6
8	10	200	2
10	8	200	2
9	15	150	5
15	9	150	5
9	16	100	3
16	9	100	3
10	12	100	3
12	10	100	3
10	13	200	4
13	10	200	4
11	23	150	15
23	11	150	15
11	40	100	9
40	11	100	9
12	13	100	8

From Node	To Node	Arc Capacity	Lead Time
13	12	100	8
12	18	100	6
18	12	100	6
12	40	100	8
40	12	100	8
13	19	200	5
19	13	200	5
14	15	150	1
15	14	150	1
14	19	150	4
19	14	150	4
14	20	100	9
20	14	100	9
15	16	100	5
16	15	100	5
15	21	250	9
21	15	250	9
16	17	100	8
17	16	100	8
16	21	100	12
21	16	100	12
17	22	100	11
22	17	100	11
18	19	100	11
19	18	100	11
18	24	100	12
24	18	100	12
19	25	200	12
25	19	200	12
20	21	100	5
21	20	100	5
20	26	100	8
26	20	100	8
21	22	100	3
22	21	100	3
21	46	250	9
46	21	250	9
22	46	150	5
46	22	150	5
23	24	200	11
24	23	200	11
24	25	200	13
25	24	200	13
25	26	150	1

From Node	To Node	Arc Capacity	Lead Time
26	25	150	1
25	38	200	13
38	25	200	13
26	27	150	2
27	26	150	2
27	28	150	5
28	27	150	5
27	31	100	4
31	27	100	4
28	29	150	1
29	28	150	1
28	45	100	2
45	28	100	2
28	46	100	4
46	28	100	4
29	30	200	3
30	29	200	3
29	33	250	7
33	29	250	7
29	46	250	3
46	29	250	3
30	32	100	3
32	30	100	3
31	39	100	11
39	31	100	11
31	45	100	3
45	31	100	3
32	34	100	5
34	32	100	5
32	45	100	4
45	32	100	4
33	35	100	2
35	33	100	2
33	36	250	2
36	33	250	2
34	35	100	2
35	34	100	2
34	39	100	10
39	34	100	10
34	47	100	3
47	34	100	3
35	47	100	3
47	35	100	3
36	37	250	1

From Node	To Node	Arc Capacity	Lead Time
37	36	250	1
36	43	100	5
43	36	100	5
37	44	250	3
44	37	250	3
38	39	200	1
39	38	200	1
39	41	200	6
41	39	200	6
47	41	100	2
41	47	100	2
47	42	100	3
42	47	100	3
41	42	200	2
42	41	200	2
42	43	200	1
43	42	200	1
43	44	200	1
44	43	200	1

Table A.2. Node data of the Monticello, Minnesota nuclear power plant modified to include the emergency first responder population.

Node	Node Capacity	Evacuee Initial Population	Responder Initial Population
1	9999999	0	0
2	2400	2354	0
3	3500	3408	0
4	2300	2236	0
5	800	707	0
6	4700	4616	0
7	250	0	0
8	250	0	0
9	6800	6749	0
10	4000	3994	0
11	250	0	20
12	250	0	0
13	250	0	0
14	4700	4675	0
15	250	0	0
16	250	0	0
17	250	0	20
18	1800	1785	0
19	9700	9645	0
20	250	0	0
21	1400	1390	0
22	250	0	0
23	250	0	0
24	250	0	0
25	250	0	30
26	250	0	0
27	250	0	0
28	250	0	0
29	250	0	0
30	250	0	0
31	250	0	0
32	250	0	0
33	250	0	20
34	250	0	0
35	250	0	0
36	250	0	0
37	250	0	0
38	250	0	50
39	250	0	0
40	400	391	0

Node	Node Capacity	Evacuee Initial Population	Responder Initial Population
41	250	0	0
42	250	0	20
43	250	0	40
44	250	0	20
45	250	0	0
46	250	0	0
47	99999999	0	0

APPENDIX B:
BEST NETWORK CONFIGURATION FROM THE PROPOSED GENETIC-BASED SOLUTION PROCEDURE

Table B.1. Best network configuration found by the GA-based approach at parameter settings $P = 200$, $G = 500$, $p_c = 85\%$ and $p_m = 1\%$. (Replication 13).

From Node	To Node	Arc Capacity	Lead Time	Arc Direction (1 = Normal Flow Direction)
1	2	41950	0	0
2	1	41950	0	1
2	3	150	18	1
3	2	150	18	1
2	4	150	9	0
4	2	150	9	1
3	5	250	6	0
5	3	250	6	0
3	6	150	5	0
6	3	150	5	0
4	5	100	17	0
5	4	100	17	0
4	7	150	10	0
7	4	150	10	1
4	10	100	15	1
10	4	100	15	1
5	16	250	11	1
16	5	250	11	0
6	9	200	9	0
9	6	200	9	0
7	10	150	8	1
10	7	150	8	0
7	18	100	7	0
18	7	100	7	1
8	9	150	17	0
9	8	150	17	0
8	12	150	6	1
12	8	150	6	1
9	11	200	2	0
11	9	200	2	0
10	16	150	5	1
16	10	150	5	1
10	17	100	3	0
17	10	100	3	1
11	13	100	3	0

From Node	To Node	Arc Capacity	Lead Time	Arc Direction (1 = Normal Flow Direction)
13	11	100	3	0
11	14	200	4	0
14	11	200	4	1
12	24	150	15	1
24	12	150	15	1
12	41	100	9	0
41	12	100	9	0
13	14	100	8	1
14	13	100	8	0
13	19	100	6	1
19	13	100	6	1
13	41	100	8	1
41	13	100	8	0
14	20	200	5	1
20	14	200	5	0
15	16	150	1	0
16	15	150	1	1
15	20	150	4	0
20	15	150	4	1
15	21	100	9	1
21	15	100	9	0
16	17	100	5	1
17	16	100	5	0
16	22	250	9	1
22	16	250	9	0
17	18	100	8	0
18	17	100	8	0
17	22	100	12	0
22	17	100	12	1
18	23	100	11	0
23	18	100	11	1
19	20	100	11	1
20	19	100	11	0
19	25	100	12	1
25	19	100	12	1
20	26	200	12	0
26	20	200	12	0
21	22	100	5	1
22	21	100	5	0
21	27	100	8	0
27	21	100	8	1
22	23	100	3	0
23	22	100	3	0

From Node	To Node	Arc Capacity	Lead Time	Arc Direction (1 = Normal Flow Direction)
22	47	250	9	0
47	22	250	9	0
23	47	150	5	0
47	23	150	5	1
24	25	200	11	1
25	24	200	11	1
25	26	200	13	0
26	25	200	13	1
26	27	150	1	0
27	26	150	1	0
26	39	200	13	1
39	26	200	13	0
27	28	150	2	1
28	27	150	2	1
28	29	150	5	0
29	28	150	5	0
28	32	100	4	0
32	28	100	4	1
29	30	150	1	1
30	29	150	1	1
29	46	100	2	1
46	29	100	2	1
29	47	100	4	0
47	29	100	4	1
30	31	200	3	1
31	30	200	3	1
30	34	250	7	1
34	30	250	7	0
30	47	250	3	0
47	30	250	3	0
31	33	100	3	0
33	31	100	3	0
32	40	100	11	1
40	32	100	11	0
32	46	100	3	0
46	32	100	3	1
33	35	100	5	1
35	33	100	5	0
33	46	100	4	1
46	33	100	4	0
34	36	100	2	0
36	34	100	2	0
34	37	250	2	1

From Node	To Node	Arc Capacity	Lead Time	Arc Direction (1 = Normal Flow Direction)
37	34	250	2	1
35	36	100	2	1
36	35	100	2	0
35	40	100	10	0
40	35	100	10	0
35	48	100	3	1
48	35	100	3	0
36	48	100	3	1
48	36	100	3	1
37	38	250	1	1
38	37	250	1	1
37	44	100	5	0
44	37	100	5	1
38	45	250	3	0
45	38	250	3	0
39	40	200	1	1
40	39	200	1	0
40	42	200	6	1
42	40	200	6	0
48	42	100	2	1
42	48	100	2	1
48	43	100	3	1
43	48	100	3	1
42	43	200	2	1
43	42	200	2	0
43	44	200	1	1
44	43	200	1	0
44	45	200	1	1
45	44	200	1	1
48	49	41950	0	1
49	48	41950	0	1

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