Development of a Mass Evacuation Decision Support Tool

by

MD Jahedul Alam

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Dedicated to

My precious baby

Jayan

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Abstract

This study presents a sequential modelling framework of a mass evacuation decision support (MEDS) tool and develops countermeasures to improve mass evacuation processes. The study develops a large-scale traffic evacuation microsimulation model to design, test and evaluate contrasting evacuation scenarios, and evacuation improvement strategies, alternatively countermeasures. One of the notable contributions of this study is that it combines a flood risk and a traffic microsimulation model to assess evacuation operations under floods of different extremes. The microsimulation model uses evacuation demands obtained from a Halifax regional transport network model and considers a dynamic traffic assignment process to capture time-dependent traffic congestion propagation in the network. The study extends the microsimulation model by the inclusion of a transit network to meet the transportation needs of the transit-dependent population during evacuation. The study develops a Mixed Integer Linear Programming-based optimization model to identify marshal point locations and transit routes for a multimodal evacuation. The study leverages the simulation model to analyze further complexity, including vehicle collision-related traffic disruptions during evacuation. A combined Bayes theory and Monte Carlo simulation approach is adopted to determine the spatial and temporal distribution of collision hotspots and their occurrence during evacuation. The application of the developed modules has been instrumental in the design and implementation of countermeasures. The study designs, implements, and evaluates two strategic level countermeasures, namely staged and bus-based evacuation. The study innovates a fuzzy logic-based prioritization process for a staged evacuation based on the zonal vulnerability index. The study develops a Bayesian Belief Network-based vulnerability assessment model that provides a combined zonal vulnerability index considering geophysical, social and mobility characteristics. The study formulates a Knapsack optimization problem following a dynamic programming solution approach to allocate buses to evacuees. The uniqueness of the countermeasures developed in this research is that they ascertain a vulnerability-based prioritization of evacuees for evacuation. The countermeasures offer promising results in terms of evacuation time and network congestion improvements within the traffic microsimulation model. The MEDS tool will be helpful for emergency engineers and planners to understand potential impacts of wide-ranging magnitudes associated with a mass evacuation and plan mitigations proactively.

List of Abbreviations and Symbols Used

Abbreviations

AGRG : Applied Geomatics Research Group

AHP : Analytical Hierarchy Process

AIMSUN : Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks

AMAM : All Mode Allocation Module

BBN : Bayesian Belief Network

BN : Bayesian Network

CGVD : Canadian Geodetic Vertical Datum

CI : Consistency Index

CORSIM : CORridor SIMulation

CPT : Conditional Probability Table

CR : Consistency Ratio

DalTRAC : Dalhousie Transportation Collaboratory

DEM : Digital Elevation Model

DP : Dynamic Programming

DT : Downtown

DTA : Dynamic Traffic Assignment

DYNASMART-P : Dynamic Network Assignment-Simulation Model for Advanced Road Telematics

DYNEV : Dynamic Network Evacuation Model

DynusT : Dynamic Urban Systems for Transportation

EMO : Emergency Management Organization

EPZ : Emergency Planning Zone

GIS : Geographic Information System

HHWLT : Higher High-water at Large Tide

HRM : Halifax Regional Municipality

ILUTE : Integrated Land Use, Transportation,and Environment

iTLE : Integrated Transport Land Use and Energy

LHS : Latin Hypercube Sampling

LiDAR : Light Detection and Ranging

LP : Linear Programming

MASSVAC : Mass Evacuation Computer Program

MEDS : Mass Evacuation Decision Support Tool

MILP : Mixed Integer Linear Programming

MIP : Mixed Integer Programming

MNL : Multinomial Logit Model

MPL : Mathematical Programming Language

NAD : North American Datum

NE : North-End

NETVAC : Network Emergency Evacuation Model

NRN : National Road Network

NS : Nova Scotia

NSCC : Nova Scotia Community College

NSCRD : Nova Scotia Collision Record Database

OREMS : Oak Ridge Evacuation Modelling System

PADM : Protective Action Decision Model

PARAMICS : Parallel Microscopic Simulation of Road Traffic

RESCUE : Agent-based Regional Evacuation Simulator

RI : Average value of Consistency Index

SE : South-End

SNSMR : Service Nova Scotia and Municipal Relations

TAZ : Traffic Analysis Zone

TRANSIM : Transportation Analysis and Simulation System

TRB : Transportation Research Board

UTM : Universal Transverse Mercator

VBA : Visual Basic for Applications

VISSIM : Verkehr In Städten – SIMulationsmodell (i.e., Traffic in cities – simulation model)

VISUM : Macroscopic Traffic Simulation Software

WE : West-End

Symbols

$T_i^{q,e}$: Smoothed travel time

$TC_i^{q,e}$: Measured travel time

e : Evaluation interval index

q : Iteration index

i	: Link edge index
Q	: Importance of measurement of the distant iteration
ax	: Average standstill distance
bx_add	: Additive part of safety distance
bx_mult	: Multiplicative part of safety distance
d	: Safety distance
z	: Random values for safety distance calculation
v	: Vehicle speed in safety distance calculation
z	: Represent a TAZ in MILP model
s	: Represent a bus stop
q_s	: Bus stop capacity
y_{zs}	: Binary variable to choose a bus stop
$d_{threshold}$	: Threshold walking distance from zone to bus stop
x_{zs}	: Demand from a zone to a bus stop
D_z	: Transit demand of a zone
R	: Set of transit routes
M	: Set of marshal points
a_{nr}	: Binary variable to choose a marshal point on a bus route

p_r	: Binary variable to choose a transit route
r_i	: Route ID index
$V_{factors}$	: Set of factors influencing vehicle collision occurrence
L	: Set of candidate collision locations
l_i	: Location IDs in the set of candidate collision locations
$E_{veh.coll}$	: Represent an event involving vehicle collision
$E_{other.coll}$	: Represent an event involving non-vehicle collision
$P(l_{i,veh.coll})_{V_{factors}}$	: Probability of observing a location for collision
p_i	: Probability criteria
$L_j^{p_i}$	: set of all candidate collision location subsets
$\left(L_{T_t}\right)^{p_i}$	: Set of all hotspot subsets
$\phi_{simulated}$	: Simulated collision occurrence distribution at hotspots
$\phi_{observed}$	: Observed collision occurrence distribution at hotspots
T_t	: Evacuation hours
r	: Monte Carlo simulation run index
ζ	: Threshold value for Monte Carlo simulation validation
v_i	: Node IDs in BN network

V	: Set of all nodes in BN network
$p(v_i \mid E)$	: Conditional probability of v_i given the evidence E
$\gamma_{\max}$	: Largest eigen value
η	: Number of rows and columns in the comparison matrix
x_{ij}	: Cell value in the comparison matrix
$\mu(x)$	: Membership value
x	: Element of fuzzy membership function
ψ^*	: Crisp output value in defuzzification
R^2	: Goodness-fit-of-the-model
W	: Bus capacity
I	: Set of individuals
i	: Departure time segment in AMAM
v_i	: Vulnerability score in AMAM

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Chapter 1

Introduction

1.1 Background and Motivation

Evacuation is an important process to collectively move people from an area endangered by a natural or manmade disaster using multiple transportation modes and evacuation routes. The last several decades are known for many record-breaking hurricanes and evacuation events worldwide. Hurricane Katrina in 2005 was a Category 5 Atlantic Hurricane which made a landfall at Hallandale Beach and mainly devasted the city of New Orleans and adjacent areas. Katrina evacuation was criticized as unsuccessful by many stakeholders as it was poorly planned; for instance, the transit dependent population did not receive adequate attention in evacuation planning (Renne et al., 2011). Approximately one-third population of the city did not evacuate for several reasons, including lack of access to reliable transportation modes (Litman, 2006; Renne and Mayorga, 2018). During Hurricane Rita in 2005, 3 million people evacuated from Louisiana and Texas creating a 100-mile-long traffic queue that left many people stranded on the roads for 10-12 hours and caused people to run out of fuel (Litman, 2006; Blumenthal, 2005). The estimated automobile evacuation time along the South Carolina Coast during Hurricane Florence was 36 to 48 hours (Marshall, 2018). Hurricane Florence caused more than 42 deaths and almost $50 billion USD economic damages in North and South Carolina and Virginia. The highest economic damage was caused by the Hurricane Katrina and Hurricane Harvey, which was $125 billion USD for each. These events resulted in mass evacuations, for example, in the state of Louisiana, around 1.7 million people evacuated during Hurricane Katrina 2005, while in Florida 6.5 million people were under mandatory or voluntary evacuations during Hurricane Irma 2017. Over 1.7 million people were evacuated from North and South Carolina and Virginia due to Hurricane Florence. Very recently, Hurricane Delta and Hurricane Laura hit the northern Gulf as Category 2 and Category 4 respectively with record surge and high wind. Hurricane Delta unleashed 9-foot surge and 16-inches of rain this year.

The natural and manmade disasters are not uncommon in Canada. In May 2019, the Chuckegg Creek wildfire spread into northern Alberta, Canada and grew triple in size in fewer than 24 hours. Around 3,000 people were told to evacuate from the affected area and be away for at least 72 hours. Eventually, the fire burned through 99,250 hectares of North Alberta land and destroyed over a dozen of homes (Short, 2020). One of the most significant and costly disasters in Canada is the Fort McMurray wildfire which caused a rapid evacuation of 88,000 people and $3.5 billion USD in insured losses (Mamuji, and Rozdilsky, 2019). While the West Coast of Canada is at risk of catastrophic wildfires, communities on the East Coast are vulnerable to hurricanes and floods. For example, Halifax has been imperiled by several catastrophic natural disasters, including Hurricane Juan 2003 and Hurricane Dorian 2019. The storm surge recorded during Hurricane Juan was between 2.04m and 2.11m. It caused eight fatalities and over $300 million CAD in damage across parts of Atlantic Canada (Fogarty, 2003). Hurricane Dorian caused a crane to collapse onto a building that was under construction, cracking the crane in half. The hurricane left 80% of customers of Nova Scotia Power in the province without electricity (The Canadian Press, 2019). Historically, Halifax was also devastated by an explosion in 1917 when a French Cargo ship collided with a Norwegian vessel in a strait connecting upper Halifax Harbour to Bedford basin. Approximately 2000 people died and 9000 were injured in this disaster (The Editors of Encyclopaedia Britannica, 2008). Large-scale evacuations due to disasters create miles of traffic congestions in the network. In case of certain evacuation cases, the condition worsens due to the lack of adequate planning, vehicle collisions and incidents as occurred during Hurricane Katrina, Hurricane Rita, Hurricane Irene, and Sandy. During Hurricane Harvey, people who chose not to evacuate trapped in their residents as there were no access points available to rescue them due to flooding. It is evident that evacuation is a process consisting of multiple interrelated aspects and therefore, there is a need to systematically understand the intricacies around evacuations for better preparedness and response during any disaster.

Evacuation itself is a complex process. Although a mass evacuation is an uncertain event, traffic models can be an efficient tool to understand and analyze an evacuation operation. Information obtained from these models can assist in emergency planning and decision-making process. However, evacuation modelling is sophisticated as the evacuation process is susceptible to multiple disruption risks in the network. Moreover, other parameters, including network structures, vulnerable populations, and resource constraints are of concern when planning a mass evacuation. For example, the Halifax Peninsula in Canada has only five exit/entry points which poses threat to the network itself. This region is on hurricane path and susceptible to flooding. Affluence and poverty co-exist in this area. Being a historical city with narrow roads, the area faces mobility challenges during peak hours. Therefore, people exposed to geophysical, social, and mobility vulnerabilities in the peninsula may need prioritized evacuations or assistance with transportations. For example, evacuees with no vehicles may need to be evacuated first and it may require deploying other available modes in combination with automobiles for transit-dependent population and those who do not have easy access to personal vehicles. Particularly, transit and school buses are important not only for arranging transportation for those in need but also for best utilizing the network capacity and minimizing traffic congestions in the network. One of the successful utilization of transits was in the evacuation of the World Trade Center and its surrounding area due to the 9/11 terrorist attack in New York (Cavusoglu et al., 2013). Although the transit needs have been realized, it is still the most neglected element of evacuation planning (Clark and Habib, 2010). However, it urges to explore the unaddressed topics of a mass evacuation to understand its complex process. Therefore, there is a need of a flexible evacuation decision support tool that considers disruptions, and uncertainties to provide a holistic view to evacuation planning.

To articulate a realistic and a comprehensive evacuation scenario within the evacuation modelling framework, it is imperative to capture multi-layer risks and uncertainties associated with a mass evacuation. The existing evacuation studies explored different challenges in evacuation independently, such as traffic congestions (Naghawi and Wolshon, 2011), road network disruptions due to explosion (Bae et al., 2014), among others. On the other hand, several researchers (Li et al., 2012a; Kaisar and Parr, 2012; Wang et al., 2014) evaluated different strategies towards improving evacuation times and traffic congestions in the network. However, most of these studies are automobile-based, and experimental in nature, focused on highway corridors or small area evacuations. These studies did not explicitly consider traffic disruption risks and uncertainties in evacuation analysis. A large-scale traffic evacuation microsimulation model appears to be advantageous to address the current modelling issues as it is capable to track each vehicle or agent evacuating through the network, capture continuous changes in traffic conditions and the resulting driver's routing policies through implementing a dynamic traffic assignment (DTA) process. A DTA-based traffic microsimulation model allows the manifestation of multi-faceted evacuation operations in the network. However, evacuation scenario testing considering different types of traffic disruptions and vulnerabilities requires further modelling efforts, including the development and coupling of multi-layer modules within a robust evacuation modelling framework. The coupling of different evacuation modules ensures that the impact of an evacuation parameter is carried forward to the estimation of other interrelated parameters. Moreover, it widely opens the scope of each module for other large-scale modelling applications when combining within a robust evacuation modelling tool. For example, a flood risk model can be combined with a traffic simulation model to estimate the flooding related impacts on overall evacuation operation in the network. The outcome of the modules can further inform different planning decisions and countermeasure building process. Literature suggests that without any countermeasure applied, conventional evacuation generally associates spontaneous behavior of evacuees leading to disorganization and consequently to a prolonged and/or incomplete evacuation. Therefore, it prompts a more efficient evacuation system, particularly for areas that contain vulnerable populations who are at high-risk and need a priority-based evacuation. This study considers two countermeasures, namely staged and bus-based evacuation. Staged evacuation is a useful tool to maintain a priority-based entry of evacuation traffic to the network and thereby minimizes traffic congestions and evacuation times. The latter countermeasure considers transit and school buses for evacuation through developing an all-mode evacuation scenario. The countermeasures developed in this research ascertain a vulnerability-based prioritization of evacuees during a mass evacuation.

In summary, it is evident that evacuation is convoluted by many factors of different levels and impacts, and it warrants the development of a comprehensive evacuation decision support tool that combines multiple modules to represent multi-layer complexities associated with a mass evacuation operation. The research addresses the current modelling issues by developing the abovementioned core components following cutting-edge modelling approaches and combining them within the proposed holistic evacuation modelling framework.

1.2 Objectives

The overall goal of this research is to develop a comprehensive framework for a mass evacuation decision support tool that combines multiple modules to address multilayer complexities in assessing contrasting evacuation and countermeasure scenarios. To achieve the goal, the study would accomplish the following specific objectives.

1. To conceptualize a framework for mass evacuation decision support tool.
2. To develop a multimodal traffic evacuation microsimulation model that considers a dynamic traffic assignment process.
3. To expand the mass evacuation decision support tool to incorporate a multitude of risks including vehicle collision.
4. To develop countermeasure scenarios considering vulnerabilities to improve mass evacuation processes.

Objectives 1, 2, and 3 are addressed in chapter 4, 5, and 6. Objective 4 regarding countermeasures is explored in chapter 7, 8, and 9.

1.3 Significance

This study contributes to the field of evacuation research focusing on evacuation modelling that accounts for multi-layer complexities in evacuation scenario analysis. The study aims to resolve the existing evacuation modelling issues and ascertain vulnerability-based prioritization of the affected population for evacuation when evaluating countermeasure scenarios. This research develops an evacuation decision support tool that provides wide-ranging flexibility to test and evaluate contrasting evacuation scenarios. The tool would help emergency planners better prepare for a mass evacuation of the city and possibly save lives. Emergency planners can use the tool to change different evacuation parameters to create numerous evacuation scenarios to understand the challenges and develop plans to accelerate evacuation efforts. The tool will not only identify traffic operation challenges but also explore the variables of interests, and improvement strategies. Planners can test and evaluate different strategies such as setting all lanes outward from the evacuation point to the destination, changing traffic signal timing, optimizing marshal point locations for bus evacuation, among others. The study considers the Halifax Peninsula, a Canadian coastal community, as a case study to demonstrate the efficacy of the proposed evacuation modelling tool. The Halifax Peninsula has only five exit points which poses risk to the network itself and makes it vulnerable during a disaster. Moreover, the peninsula's narrow roads and lack of sufficient highways would make an evacuation particularly difficult. Although, this research demonstrates the successful application of the evacuation decision support tool for Halifax, the scenarios could be adapted to create simulations useful to planners in other parts of the country.

1.4 Thesis Structure

This thesis is comprised of ten chapters. Chapter two provides an overview of evacuation modelling, reviews the relevant studies, including evacuation behavior modelling, evacuation operation optimization and simulations, and countermeasure development. This chapter, through an extensive literature review, identifies the research gaps followed by stating research questions and concluding remarks.

Chapter three discusses the conceptual framework of a mass evacuation decision support (MEDS) tool. The chapter describes different modules of the tool and their roles in incorporating risks and uncertainties within the evacuation modelling framework.

Chapter four focuses on the traffic microsimulation modelling of evacuation scenarios considering floods of different extremes. The chapter includes a synthesis of literature review in the field of traffic evacuation simulations to identify the room for methodological contributions. It presents a sequential modelling approach to combine a Halifax road network and a flood risk model with a traffic evacuation microsimulation model. It also describes the development process for each component. Furthermore, the chapter involves a discussion on the model results such as evacuation times, traffic congestions, evacuation completion and network performances for three flooding related evacuation scenarios.

Chapter five explores multimodal evacuation. Transit buses are utilized in combination with automobiles to meet the transportation needs of the transit-dependent population during evacuation. It first develops a Mixed Integer Linear Programming (MILP) model to optimize marshal point locations and transit routes to inform traffic microsimulation model for multimodal evacuation scenarios. The chapter presents an analysis of multimodal evacuation results and highlights the potential adaptive capacity of buses that can be used to accommodate for evacuees shifted from other modes of transportation.

Chapter six presents a framework of traffic evacuation microsimulation modelling that accounts for network disruptions due to the risks inherent to traffic operation such as vehicle collision. The chapter presents a coupling of collision prediction and traffic microsimulation model to test and evaluate five different evacuation scenarios considering uncertain traffic disruptions. Finally, the chapter discusses the scenario outcomes and includes a conclusion.

Chapter seven presents a framework of vulnerability assessment modelling in the context of a mass evacuation. The chapter demonstrates a coupling of a flood risk model, a population synthesis, and the traffic microsimulation model to incorporate geophysical, social, and mobility characteristics in zonal vulnerability assessment. It identifies the factors influencing vulnerabilities and discusses the variations in vulnerabilities across the study area.

Chapter eight presents the traffic microsimulation of a countermeasure, namely "staged evacuation". The chapter presents a fuzzy logic-based staged evacuation model that informs a staged evacuation scenario within the traffic microsimulation model. The chapter also includes an evacuation scenario analysis when no coordination or countermeasure is applied. It presents a comparative analysis of evacuation as well as network performances for both simultaneous and staged evacuation scenarios. The novelty of this countermeasure is that it develops a prioritization process for staged evacuation. The chapter provides policy insights highlighting the need of integrating other different countermeasures with staged evacuation.

Chapter nine describes a countermeasure that involves transit and school buses in combination with private cars in evacuation operations and is known as "bus-based evacuation". The chapter presents an optimization model to allocate transit and school buses to evacuees based on the vulnerabilities that they are exposed to. It discusses the improvement in evacuation times and network congestion due to the inclusion of transit and school buses in combination with passenger cars.

Finally, chapter ten includes a summary of the key research findings, and policy recommendations, a list of contributions, and offers insights towards future research directions.

Chapter 2

Literature Review

2.1 Introduction

This chapter synthesizes evacuation studies to provide an overview of evacuation research and modelling efforts made to date and to identify the gaps in this research field for contributions. Evacuation research has evolved in multiple directions and developed numerous evacuation models to predict, optimize, and simulate different aspects of evacuation events. The literature review in this chapter explores various evacuation research directions, modelling techniques utilized, and evacuation improvement strategies developed. A set of broader research questions are identified based on the literature review in this chapter. In addition to this literature review, each chapter onwards includes the review of existing evacuation studies to identify the specific gaps and enable methodological contributions.

2.2 An Overview of Evacuation Research and Modelling

Extreme weather events such as hurricane and flooding have become increasing risks in many coastal cities world-wide. Natural disaster has increased threefold since 1975 and the cities have faced enormous risks from Hurricane Katrina, Hurricane Rita, Hurricane Irma, Hurricane Harvey, Hurricane Florence, and Hurricane Michael. Hurricane Dorian, a Category 5 Atlantic Hurricane, hit the Bahamas in 2019. It transitioned to an extratropical cyclone and strike Nova Scotia. About 80% of NS residents were without power and uprooted trees and fallen crane blocked major transportation routes. The most damaging NS hurricane in last century is

Hurricane Juan that unleashed the highest storm surge (Forbes et al., 2009). Significant research on weather forecast is accomplished. There are two weather forecast models such as European model known as European Center for Medium-Range Weather Forecasts (ECMWF), and American model which is called Global Forecast System (GFS) model. The models reliably forecast hurricane landfall in advance of 10 and 16 days, respectively. The forecast is useful to reduce risks, enhance emergency preparedness, and response. Evacuation is an effective mitigation measure during catastrophic events, be it natural or human-made. Mass evacuation research has recently gained attention and is evolving in multiple directions, including evacuation behavior analysis, and traffic evacuation operations. Evacuation behaviour analysis includes multiple resolutions of evacuation dynamics such as evacuation decisions, social network impacts, and mobilization time (Sadri et al., 2013; Sadri et al., 2017; Lindell et al., 2020). Collective evacuation decisions yield evacuation demand which is one of the key determinants influencing traffic evacuation operations. Significant studies focused on evacuation behaviour analysis such as several models (Hasan, et al., 2011; Lazo et al., 2015; Sadri et al., 2014; Sadri et al., 2015; Yang et al., 2016; Cheng et al., 2011) were developed to explore evacuee's behavior and their evacuation decisions in response to an evacuation order. These studies explored how people with different socioeconomic characteristics decide to evacuate, choose their evacuation modes and destinations in response to an emergency evacuation order. Alawadi et al. (2020) developed an evacuation model to identify the influencing factors in making partial and full evacuation decision by households and found several influential factors, including precise landfall location, age and family bond, and household types. These studies revealed that an evacuation involves spontaneous behavior of evacuees that result in a sudden spike in traffic demand in the network. However, the transport network is not designed to accommodate for the resulting mammoth traffic fleets. Furthermore, natural disasters are rare; hence, difficult to observe behavioural response. That being said, simulation technique is an effective tool to generate an understanding of the system responses. In the early stage of evacuation studies, several evacuation times estimate models were developed such as NETVAC (Sheffi et al., 1982), MASSVAC (Hobeika and Jamei, 1985; Hobeika and Kim, 1998), OREMS (Rathi and Solanki, 1993), and IMDAS (Han and Franzese, 2001). These models were developed at macroscopic level and are limited to specific emergency scenarios such as nuclear emergency. On the other hand, with the benefits of innovations in modern technology and the advancement in hardware computation ability, traffic microsimulation models have recently gained attention in evacuation studies. A study by Longo (2010) signified the use of simulation approach and models in emergency management. The author suggested that simulation forms a key method that enables understanding the complexity of a natural systems involved. Recent studies developed optimization (Sayyady and Eksioglu, 2010; Goerigk et al., 2014; Kulshrestha et al., 2014), cell-based network optimization (Liu et al., 2006; Li and Han, 2015), traffic simulation (Church and Sexton 2002; Zou et al., 2005; Li et al., 2012b), agent-based simulation (Wang et al., 2016; Chen and Zhan, 2008; Yu et al., 2018), and analytical simulation models (Chen et al., 2007; Jha et al., 2004) for testing and evaluating evacuation scenarios. A bunch of the abovementioned simulation studies adopted traffic microsimulation approaches; however, they predominantly focused on small-scale simulation such as corridor and small area evacuation which warrants the development of a city-scale traffic evacuation microsimulation model that is capable to anticipate dynamic traffic diffusion and routing policies. A dynamic traffic assignment (DTA) module is found advantageous to represent time-dependent traffic congestion propagation, dynamic route choice behavior, and to process network paths for evaluating traffic operations (Abdelghany et al., 2000; Mahmassani, 2001; Peeta and Ziliaskopoulos, 2001). Moreover, the existing studies modelled congested but undisrupted evacuation traffic flows while transport network is susceptible to uncertain disruption risks due to disasters such as hurricane, flooding, explosion, and traffic operation related disruptions, including vehicle collisions (Sohn, 2006; Tang and Huang, 2018; Bae et al., 2014). Any network disruption may significantly affect trave time reliability, prolong the evacuation time, and cause casualties (Li and Ozbay, 2015; Mostafizi et al., 2017), which highlight the importance of assessing evacuation operations in combination with traffic disruptions. Further complexity of evacuation process comprises of the vulnerable population who might need prioritized evacuation or assistance with transportation. Hurricane Katrina evacuation unfolded the consequences that might result from evacuation planning without the consideration of the vulnerable population, for example, who do not have access to transportation. Moreover, Hurricane Rita evacuation revealed that people with their personal vehicles are also vulnerable at some extent given the vehicle incidents due to fuel shortages, and engine failure (Litman, 2006; Li and Ozbay, 2015). Furthermore, people who have a low income, living in a mobile house at a densely populated and geographically high-risk area also belong to the group of the vulnerable population (Wood et al., 2010; Smith et al., 2006). Therefore, vulnerability assessment considering social, geophysical, and mobility challenges needs to be an integral part of the evacuation planning. To holistically analyze evacuation planning process, it urges to consider transportation needs, social and other vulnerabilities, and traffic disruptions within a flexible mass evacuation decision support tool.

Consideration of countermeasure is also vital in evacuation planning. Evacuation research has also been evolved around traffic operation management, including the development and implementation of evacuation countermeasures. Several studies focused on evacuation route planning and/or in combination with countermeasures such as contraflow. Contraflow involves turning one or more inbound lane(s) towards outbound to increase the roadway capacity. Cova and Johnson (2003) developed a minimum cost flow problem that determine optimal lane-based evacuation routing plan in a complex network to minimize the evacuation time. They used a mixed-integer programming platform to solve the proposed optimization problem and utilized PARAMICS to assign the evacuation demand in a sample network. Han et al. (2006) analyzed the evacuation routing methods within DYNASMART-P. This tool adopts a simulation approach where the author evaluated different scenarios such as nearest exit static routing, Interstate Highway biased static routing, one destination dynamic routing, and nearest exit dynamic routing. The results of these simulations found that specifying one destination but allowing for dynamic routing was the best method to evacuate the entire town of 382,000 people in four hours (Han et al., 2006). Wolshon et al. (2005), and Urbina and Wolshon (2003) highlighted the possible strategies and flexibility on the highway evacuation routes with multi-lanes facility. For example, one of the inbound lanes could be reversed and used as an access for emergency services if needed (Fries et al., 2011; Wolshon et al., 2005). As an extension of these studies, Fries et al. (2011) also examined the Interstate I-26 Highway evacuation route in combination with a contraflow and considered it to be the most effective evacuation route. Although traffic operation research contributions are abundant, only few studies investigated strategic level countermeasures. Particularly, developing strategies for a large network that may suffer from time-varying different levels of severity during an evacuation is of paramount importance. Staged evacuation involves sequencing of zones based on the priority needs for evacuation. This strategy can also control traffic inflows in the network, best utilizes the network capacity and thereby minimizes congestion level. A successful implementation of this countermeasure would require multilayer planning efforts to address different issues such as whom and how to prioritize for staged evacuation. There is a growing interest in studying nature, extents, procedures, and protocols in relation to staged evacuation. The existing staged evacuation studies (Zhang et al., 2014; Chiu et al., 2008; Mitchell and Radwan, 2006; Sbayti and Mahmassani, 2006; Chen, 2008) mainly focused on reducing network clearance time and improving evacuation and network performance. They mostly used one or two of the following criteria for prioritization of areas: the distance of a zone from the source of a threat, population density, destination, and shelter requirements. However, different groups of people in a region suffer from natural disasters disproportionately due to their varying socio-economic characteristics and geographical locations. During a natural or manmade disaster, people exposed to different types of vulnerabilities receive evacuation assistance to differing degrees. During Hurricane Katrina in New Orleans, 36% people did not evacuate due to having no cars, limited direct access to transportation and a lack of an effective planning to assist this group of people for evacuation. Therefore, it is of utmost importance to prioritize people for evacuation based on the vulnerabilities they are exposed to. For example, downtown of a city may require a longer clearance time due to the concentration of the economic and population growth centers and this area may need to be prioritized as first for evacuation. Furthermore, although the importance of transit in evacuation is realized since Hurricane Katrina, it is yet the most neglected and underutilized resources in meeting the transportation needs of the vulnerable population as well as in managing traffic demand in the network during a mass evacuation. Majority evacuation studies mentioned above focused on an auto-based evacuation. Several studies (Naghawi and Wolshon, 2011; Yang et al., 2018, Khulshresta et al. 2014; Sayyady and Eksioglu, 2010; Bish, 2011; Goerigk et al., 2014) developed multimodal evacuation microsimulation and optimization models to evaluate the role of transit system in evacuation. However, when considering a mass evacuation, all modes available in the network, particularly, transit and school buses may need to be deployed to evacuate a large group of population. The existing studies paid too little attention on the details of how all available modes can be optimally employed for evacuating residents based on their urgency, which warrants the development of a systematic process of bus allocation for evacuation to determine the optimum auto-bus composition in the network.

2.3 Gaps in Existing Literature

The literature review above presents a brief overview of wide-ranging evacuation modelling technique utilized in assessing contrasting evacuation scenarios. The chapter also reviewed countermeasure studies that predominantly emphasize on the highway capacity and traffic flow improvements in the network. It is evident from the literature review that despite the recent advancement in the field of traffic simulations, traffic microsimulation models are limitedly used in large-scale mass evacuation studies. The existing evacuation simulation studies involve hypothetical and/or small-scale network, conduct corridor-based evacuation analysis, and investigate different evacuation facet(s) sparsely using several independent evacuation modelling components. Moreover, the modelling scopes in these studies are kept within the auto-based evacuation and limited to specific scenario analysis. Although the significance of transit and school buses in evacuation has been realized since Hurricane Katrina 2005, most of the existing evacuation plans across North America rarely address the role of all modes in the evacuation plan (TRB, 2008). This research aims to develop a large-scale multimodal traffic evacuation microsimulation model utilizing a dynamic traffic assignment (DTA) procedure. The DTA module captures driver's route choices in response to uncertainty and risks occurrence during the evacuation. In case of a mass evacuation, the overall evacuation process is convoluted by many factors and the operation may be susceptible to multilayer risks such as flood related network connectivity losses, network constraints, uncertain network disruptions and resource limitations. Although different types of traffic disruptions and uncertainties have the potential to significantly influence the evacuation outcomes, literature review revealed that evacuation modelling very often overlooked these important aspects when assessing evacuation scenarios. The central contribution of this study is that it develops a mass evacuation decision support tool which is flexible to incorporate multiple types of disruptions and uncertainties to assess mass evacuations. This study utilizes a flood risk model that follows a digital elevation modelling approach to simulate flooding extents over a region. The model identifies the network links prone to inundation for a traffic microsimulation model. Moreover, this research develops a vehicle collision prediction model following a combined Bayes theory and Monte Carlo simulation approach to identify potential collision hotspots where the network disruptions is most likely to occur.

This chapter also discusses the studies focusing on countermeasures and asserts that the countermeasure, namely staged evacuation is limitedly addressed in the existing evacuation studies. The literature review suggests that there is a clear gap in developing a prioritization process for a staged evacuation. This study develops a fuzzy logic-based prioritization process to test a staged evacuation scenario within the traffic evacuation microsimulation model. A Bayesian Belief Network-based vulnerability assessment model is developed to inform prioritization process in this study. Lastly, a countermeasure that involves all modes, particularly transit and school buses in evacuation is absent in literature. There is a need of rolling transit and school buses in evacuation that would efficiently manage traffic demand and best use the network capacity; however, it has remained as the discussion topic for several decades. Therefor, it is important to explicitly model a bus-based evacuation. As mentioned earlier, either most of the evacuation studies are auto-based or focused on only the transit-dependent population. Moreover, the existing optimization model for bus allocation suffer from the exponential complexity and do not consider the priority needs of all evacuees within the optimization process. This research aims to develop an optimization model following a dynamic Knapsack algorithm to allocate transit and school buses to evacuees based on varying vulnerabilities that they are exposed to. The study proposes a dynamic programming to overcome the exponential complexity encountered by the existing evacuation optimization model.

In summary, although significant number of studies on different aspects of evacuation are conducted independently, a robust evacuation modelling tool is absent that can be leveraged to combine multi-layer evacuation modules to holistically assess evacuation and countermeasure scenarios considering multiple aspects.

2.4 Research Questions and Concluding Remarks

The above discussion asserts that evacuation has significantly been researched in multiple directions. However, representing multi-layer complexities of evacuation dynamics and building capacity to combine different evacuation aspects require further investigation. Particularly, this thesis looks forward to addressing the following research questions.

1. How to develop a holistic evacuation decision support tool that captures multi-layer uncertainty and risks in evacuation scenario testing and evaluation?
2. How the tool can be leveraged to inform countermeasure scenario building process while ascertaining a vulnerability-based prioritization of evacuees for evacuation and resource allocations?

This study aims to address above research questions. The study proposes a state-of-the-art mass evacuation decision support (MEDS) tool which is expected to reasonably address complexities in assessing different evacuation and countermeasure scenarios. The literature review on multiple modules is further elaborated to identify modular-specific research gaps and the room for methodological contributions in the corresponding chapters onwards. The next chapter presents a conceptual framework of the proposed evacuation decision support tool and introduces its components briefly.

Chapter 3

Conceptual Framework

3.1 Theoretical Context

The necessity of accommodating for multi-layer complexities in evacuation modelling has motivated this research to develop a mass evacuation decision support (MEDS) tool. The architecture of the proposed tool is founded on the coupling of multiple modules, while the modules exchange information through different evacuation parameters to account for multilayer uncertainty and risks in assessing evacuation scenarios within a traffic evacuation microsimulation model. The complexities in different phases of evacuation may result from natural disasters, traffic operations, special needs of the vulnerable population, and the resource constraints. It is imperative that the evacuation modelling offers a flexibility to consider these aspects when simultaneously handling a large-scale traffic evacuation in the network. The proposed MEDS tool in this research follows a sequential modelling approach that enables it to incorporate different levels of complexities in assessing contrasting evacuation plans. The research leverages the tool to develop countermeasures to better manage traffic demand and improve traffic operations during evacuation. Furthermore, the research ascertains a vulnerability-based prioritization of zones to tackle disproportionate severity across the transport network. To assess zonal vulnerability, a vulnerability assessment is conducted accounting for social, geophysical, and mobility challenges in the context of a mass evacuation. Figure 3-1 presents a conceptual framework of the proposed evacuation decision support tool that combines multiple modules discussed above.

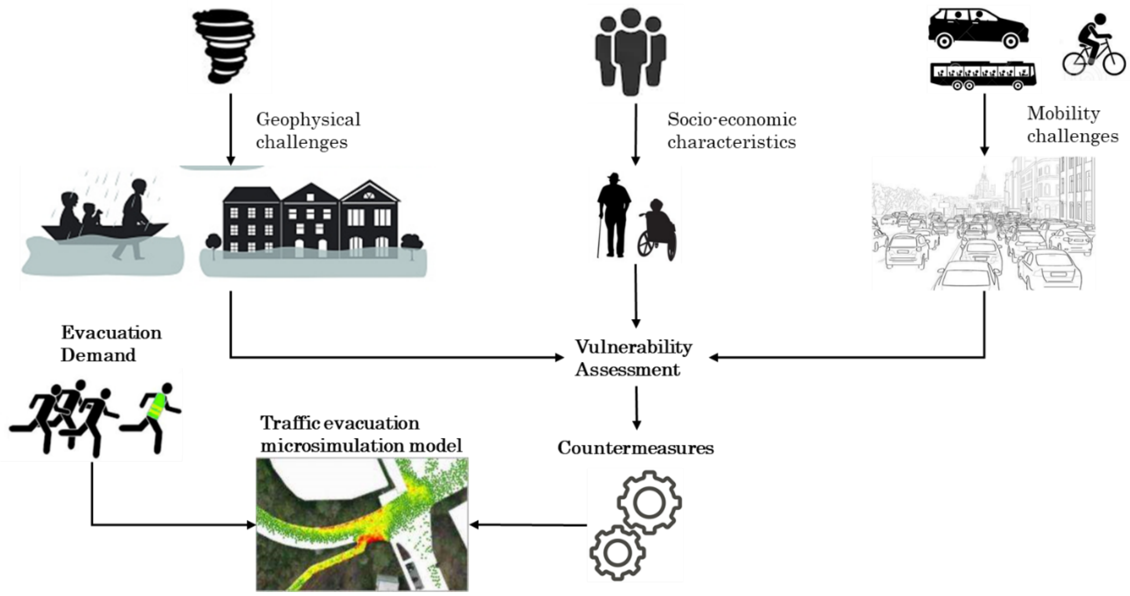

Figure 3-1 Conceptual framework of the proposed mass evacuation decision support (MEDS) tool

3.2 Modelling Framework of the Proposed MEDS tool

The proposed MEDS tool follows a sequential modelling approach to incorporate different types of traffic disruptions and uncertainties in assessing evacuation processes. The study first develops a flood risk model to identify network links prone to inundation and quantify the loss of network connectivity. Then, it develops a mass evacuation microsimulation model to assess traffic operations for the highest demand. The study explores a DTA process to capture the time-varying congestion effects and subsequent route choices within the traffic simulation model. This research leverages the microsimulation model to examine the impacts of traffic disruptions on evacuation processes. In the next phase, it inquires how to evaluate different types of countermeasures using the MEDS tool. This research considers strategic level countermeasure, namely staged evacuation. It also considers transit and school buses for evacuation through developing an all-mode evacuation process. The tool estimates evacuation demand utilizing a Halifax regional transport network model (Bela and Habib, 2018). The traffic microsimulation model is coupled with a flood risk model, and a vehicle collision prediction model to incorporate traffic disruptions in the evacuation simulation process. The proposed modular-based evacuation decision support tool is further utilized to inform countermeasure development process with information regarding the flooding, traffic operation risks, and the vulnerabilities that people are exposed to. A vulnerability assessment model is developed to holistically assess geophysical, social, and mobility vulnerability and determine a combined zonal vulnerability index. Figure 3-2 presents the modelling framework of the proposed evacuation decision support tool demonstrating the coupling of different modules.

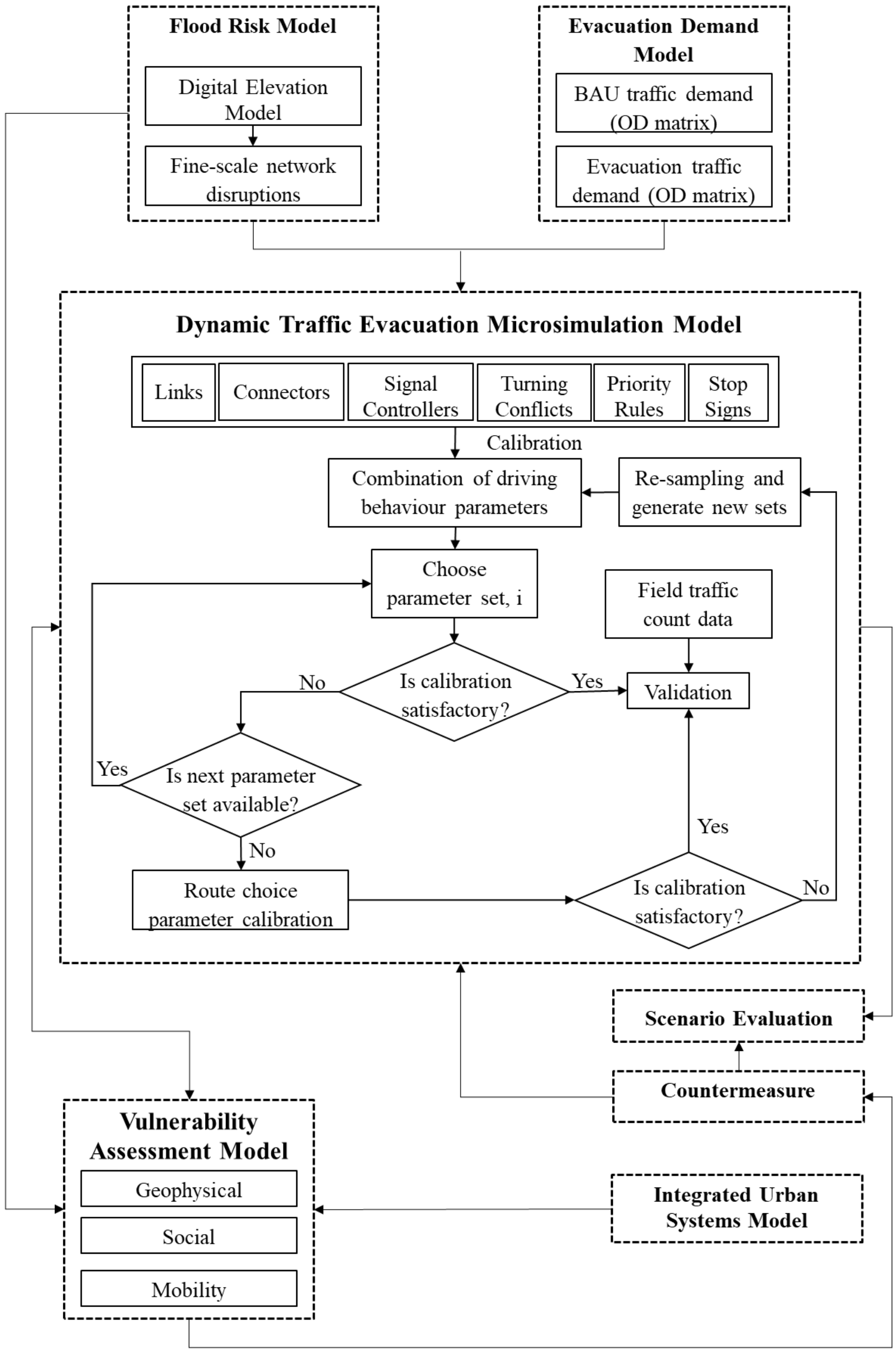

Figure 3-2 Modelling framework of the proposed mass evacuation decision support (MEDS) tool

3.2.1 Evacuation Demand Estimation

The Halifax transport network model is utilized to estimate evacuation demand in the network. The model generates 24-hour origin-destination (OD) travel demand matrices for both auto and buses. Origin and destination refer to traffic analysis zone (TAZ) in this model. The model includes a transport network of 219 traffic analysis zones, 219 zonal centroids, 2249 link nodes, and 2985 truck permitted links out of 5232 directional links. Among 219 TAZs, 93 are urban, 93 are suburban and 33 are rural.

3.2.2 Flood Risk Model

The study utilizes a flood risk model (Macdonald and Webster, 2016) to identify the network links prone to inundation during floods of different extremes. The model considers five flooding scenarios to determine the extent of the impacts of flood over Halifax region. The scenario outcomes include the extent of inundation by road classes, length, and inundation depths. The information regarding network damages is utilized within the traffic evacuation microsimulation model to capture natural disaster related impacts on the evacuating traffic flows.

3.2.3 Vulnerability Assessment Model

The vulnerability assessment model utilizes factors affecting social, geophysical, and mobility challenges to assess vulnerabilities of TAZs following a probabilistic approach. This model takes inputs from a flood risk model, a population synthesis (Fatmi et al., 2017; Fatmi and Habib, 2018), and a traffic evacuation microsimulation model to compute the combined zonal vulnerability index.

3.2.4 Evacuation Scenario Development

This research develops contrasting evacuation scenarios for testing and evaluation within the traffic evacuation microsimulation model. The proposed tool is first utilized to evaluate a base case scenario representing an evacuation when no disruption risks nor complexities are considered. The study utilizes the flood risk model to develop three evacuation scenarios that accounts for network disruptions due to floods of different extremes. Afterwards, a collision prediction model is developed to identify the collision hotspots during an evacuation and five more disruptive evacuation scenarios are derived from assorted vehicle collisions. All scenarios are accommodated within the traffic microsimulation model for testing and evaluations.

3.2.5 Countermeasure Scenario Development

The study further focuses on developing countermeasure scenarios to investigate the effects of different improvement strategies on the evacuation and network performances. Two countermeasures that operate at the strategic level 'staged evacuation', and 'bus-based evacuation' are developed and evaluated in this study. The study accounts for different zonal vulnerabilities in assessing countermeasure scenarios within the traffic evacuation microsimulation model. For example, the research develops a novel prioritization process for staged evacuation and considers the population's vulnerabilities for prioritized resource allocation such as transit and school bus allocation for conducting an all-mode evacuation.

3.3 Conclusions

This chapter presents a conceptual framework of a mass evacuation decision support tool that combines multiple modules to holistically considers multi-layer complexities in the analysis of a mass evacuation. The tool has the capability to generate evacuation results from an aggregate level to a finer grained detail, which is critical to inform the evacuation improvement scenario-building process or to resolve the modelling issues in the existing evacuation studies. The tool bridges multiple modules to facilitate an accumulation of wide-ranging inputs within a single terminator for testing and evaluation of multiple evacuation scenarios. Multiple data sources are used to develop the modules. A modular-specific literature review, data used, details of the model technicality, methodological contributions, and modular specific outcomes will be presented in the following chapters.

Chapter 4

Mass Evacuation during Flooding[1]

4.1 Introduction

This chapter presents a mass evacuation microsimulation modelling framework that accounts for flood-related network disruptions in assessing evacuation scenarios. Extreme weather events are becoming more frequent, and flooding is the most common type of natural disasters among them in Canadian cities. Examples include the Toronto flood 2013, the Halifax winter storm 2015, and Hurricane Juan 2003. Regardless of the nature of disasters, evacuation is considered an effective way to save lives when the affected zone is not safe for habitation. City evacuation is complex and a highly uncertain undertaking. Particularly, it is hard to know how traffic would flow through the transport network subjected to disruption risks, and how severe the resulting traffic congestion would be during an evacuation. Depending on the severity of a natural disaster, all network links may not be useable during an evacuation. For example, during flooding, network links are subjected to complete or partial inundation which further decreases the evacuation gateway options as well as the network capacity. Interrupted vehicle paths lead traffic to bottlenecks and degrades the overall network system efficiency.

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[1] This chapter is largely derived from the following peer-reviewed journal paper:

- Alam, M. J., Habib, M. A., Quigley, K., and Webster, T. (2018). Evaluation of the Traffic Impacts of Mass Evacuation of Halifax: A Flood Risk and Dynamic Traffic Microsimulation Modelling. *Transportation Research Record,* 2672 (1), 148-160

In this context, coastal cities such as Halifax, the capital of Nova Scotia, face considerable challenges. The Halifax Peninsula serves as the city's central business district and has only five exits/entry points. As downtown Halifax is the financial hub of the Province of Nova Scotia, its population nearly doubles during work hours. In addition, Halifax is also on a hurricane path, and extreme events such as hurricanes are common threats to the Atlantic Canada. The region has experienced natural disasters in the past that affected its critical infrastructures and the transport network. The city has two critical infrastructures, namely the Macdonald and the Mackay Bridge connecting twin cities Halifax and Dartmouth, and the low-lying transportation infrastructures such as the Bedford Highway and the Armdale Rotary. These major exit points of the peninsula are susceptible to risks of flooding or extreme winds. Given that the Halifax Peninsula provides an interesting test bed for developing a sequential evacuation modelling framework to assess flooding related network disruptions and associated challenges in a mandatory mass evacuation. The study aims to adopt a traffic microsimulation modelling approach to address the flood related network disruptions when handling and evaluating evacuation traffic flows within a traffic evacuation microsimulation model in parallel.

The main technical objectives of this study are (i) to develop a flood risk model to identify the potential network links that are prone to inundation during floods of different extremes in the Halifax Peninsula, and (ii) to develop a dynamic traffic microsimulation model to predict evacuation traffic flows considering flooding related network disruptions. The flood model informs the traffic microsimulation model regarding flood related damages to the existing Halifax transport network. The traffic simulation model utilizes a dynamic traffic assignment module (DTA) to address the routing policies, the dynamic propagation of queues and spillback in the evacuation traffic stream. The traffic assignment step uses the evacuation demand obtained from the Halifax regional transport network model (Bela and Habib, 2018).

4.2 Literature Review

Research on mass evacuation has been gaining attention in recent years to reduce loss of lives and properties during an emergency condition. Many recent disaster events have emphasized the importance of efficient and effective evacuation planning. Natural disasters are inherently rare events; they occur with potentially catastrophic consequences. Thus, it is hard in practice to quantify the extent of natural disaster related impacts on the overall evacuation process. Nevertheless, a long continuous rising trend in sea level warrants awareness on the extent and timing of coastal floods and associated damages. In this regard, high-resolution data resources of surface elevation are required for the analysis of the flood extent, associated damages, and/or for other large-scale modelling applications. In advancement with technology, the Light Detection and Ranging (LiDAR) is becoming a well-recognized data source for developing accurate surface models and providing a potential platform to develop a Digital Elevation Model (DEM) (Lohr, 1970). With the aid of a DEM, flooding limits can be mapped and analyzed in high resolution. Forbes et al. (2009) developed future extreme water level scenarios for the Halifax Regional Municipality (HRM) during floods by considering the rising mean sea level, land subsidence, storm surge, wave set up and run up, and harbor seiche. However, a hydraulically connected flood risk model is of paramount importance to predict network interruptions due to flooding at different extremes. This model then informs the microsimulation model by conveying the flood-related damages to the transport network.

Simulation-based traffic network models are very effective for formulating, implementing, evaluating, and optimizing critical traffic operations in a stochastic transport network (Ge and Menendez, 2014). These models can represent the actual traffic environment over a large network. They demonstrate an efficient traffic flow forecasting capability under critical conditions, including evacuating people to safe destinations considering flood related traffic flow disruptions. The available traffic simulation models use either static or dynamic traffic assignment (DTA) procedures to assign traffic into the network. The benefits of using DTA-based traffic simulation models is that this type of models is efficient to estimate time-dependent differential link flows in the network and generate time-dependent network performances at a fine-grained detail (Florian, 2001). Particularly, when the evacuation process is complex and traffic flow is critical during the evacuation. Therefore, advanced models including DTA-based microsimulation model are required to capture the complex interactions among vehicles, and to execute driver behavior considering all spatial attributes (e.g. paths, lane change) and temporal aspects (e.g. time-dependent congestion) under extensively congested traffic conditions in the network.

A significant research has been conducted on developing traffic simulation models for time estimates during an evacuation in the network. Sheffie et al. (1982) was the first study to develop the Network Emergency Evacuation (NETVAC) model to estimate the evacuation time in the event of an emergency at several U.S.A nuclear power plant stations. Their model determined evacuees' route choices based on the network familiarity and myopic view which can be captured by the speed on the outbound links. Dynamic Network Evacuation (DYNEV) model was developed by KLD associates (KLD Associates Inc., 1984) to estimate the network capacity and evacuation demand for nuclear power plant areas. Lieberman and Xin (2012) developed a macroscopic traffic simulation model with new features, including kinematic flow model, lane assignment model and a model to meter inflow into the links. Their model is used in DYNEV-II for large-scale evacuations, such as the evacuation of 300,000 evacuees utilizing an available highway network of 3000 links, 850 origins and 75 destinations. Though the network anticipated congestion initially, after 5 hours from the start of the evacuation, the congestion disappeared from the Emergency Planning Zone (EPZ). Chunfu et al. (2008) developed an evacuation model within the VISSIM platform to test an evacuation process for vehicles in the Beijing National Stadium's parking lots and estimated the evacuation time for all vehicles. Several evacuation studies (Bae et al., 2014; Jha eta al., 2004) have evaluated strategies involving limited access to some facilities and roads to improve both total evacuation time and the needed time to only evacuate the population within the most dangerous areas. However, most of these studies are experimental in nature or deal with limited network simulation. There is a clear gap in prediction modelling that identifies traffic impacts at city scale. In addition, calibration and validation of a large-scale evacuation microsimulation model is critical but challenging. This study proposes a process to calibrate and validate driving behavior and route choice parameters utilizing a Latin Hypercube Sampling (LHS) technique.

The modelling framework developed in this chapter fills the gap in literature by combining a GIS-based hydraulically connected flood risk model that generates fine-scale network disruptions and the microsimulation model that tests and evaluates evacuation traffic flows taking into account for flood related network disruptions. Moreover, this study examines how different levels of network damages is resulted from the flooding scenarios of different water levels, how it affects the network connectivity, and the overall evacuation performances.

4.3 Methodology

This study develops a comprehensive framework of a mass evacuation microsimulation modelling to test different evacuation scenarios in the Halifax Peninsula transport network (**Figure 4-1**).

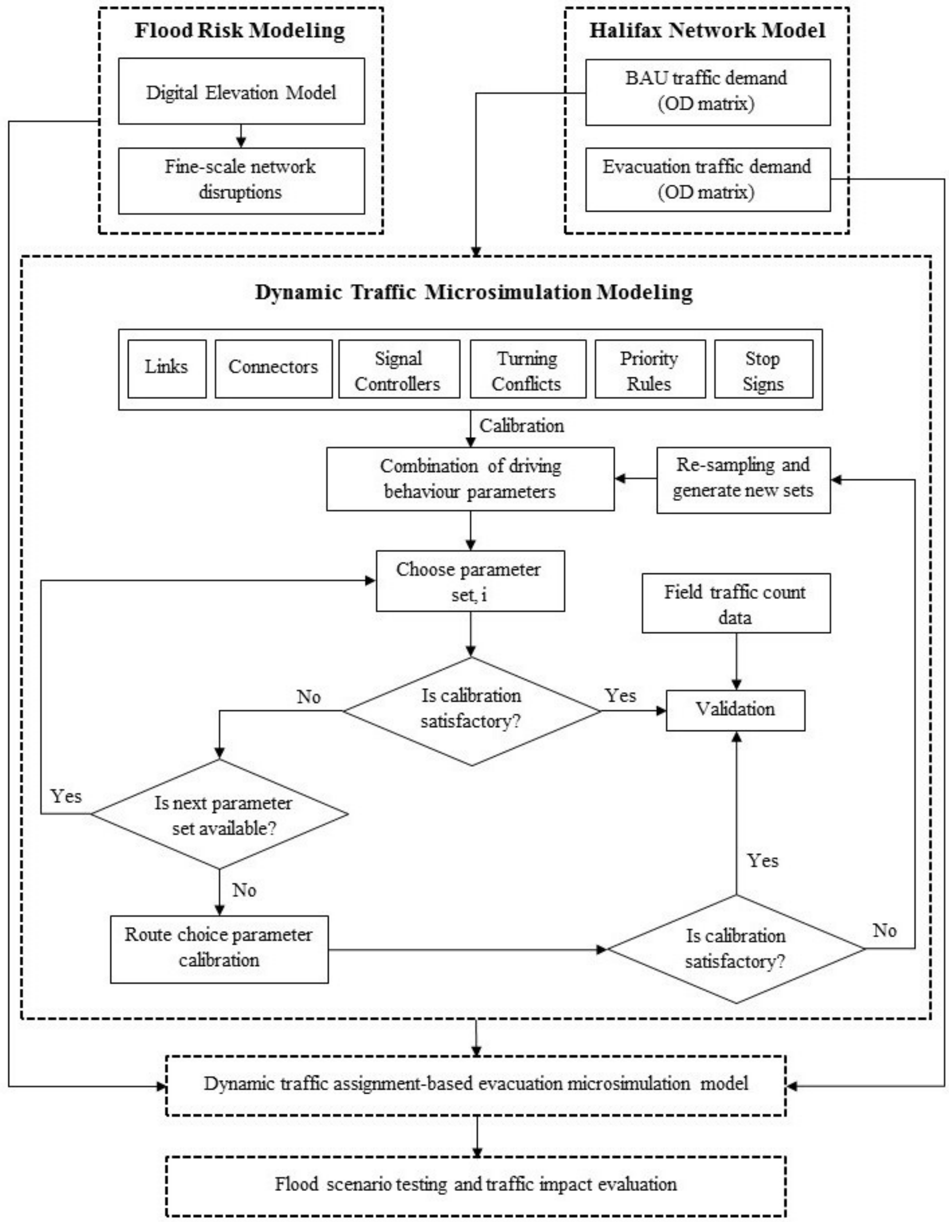


Figure 4-1 A sequential modelling framework for evacuation of the Halifax peninsula

Figure 4-1 shows a sequential modelling framework where the dynamic traffic microsimulation model recognizes the interrupted network links informed by the flood risk model and utilizes evacuation demand obtained from the Halifax regional transport network model.

4.3.1 Spatial Flood Risk Model

4.3.1.1 Data Used

The flood risk analysis requires the development of inventories of major Halifax transport network links (**Figure 4-2**) impacted under various flooding scenarios. Data used to develop the flood risk model include stream (water) network provided by the NS Topographic Database 2012 and LiDAR data obtained from the Halifax Regional Municipality (HRM). The LiDAR data is used to develop the DEM for the region. The road network data for Halifax is extracted from the National Road Network (NRN) Database 2014. All spatial data are projected in North American Datum (NAD) of 1983, Universal Transverse Mercator (UTM) zone 20 North. The vertical datum is referenced to the Canadian Geodetic Vertical Datum of 1928 (CGVD28).

4.3.1.2 Flood Layer Generation

Flood layers are generated using an Applied Geomatics Research Group (AGRG) proprietary tool that raises flood water on a flat plane (known as "still-water") to inundate low areas (Macdonald and Webster, 2016). As the tool requires an elevation model with correct connectivity, all culverts within the study area need to be represented as low areas in the DEM. First, the GIS-based tool is used to generate an initial culvert database. The culverts are then used to notch the DEM to allow a path for the water to move, resulting in a hydraulically connected DEM. The flood levels (Forbes et al., 2009) for five scenarios selected for the analysis are listed below and shown in **Appendix A (Figure A1 – Figure A3)**.

- Scenario 1 (2.9m): Water level 2.9 m relative to CGVD28, if Hurricane Juan occurred today on a higher high-water at large tide (HHWLT)

- Scenario 2 (3.9m): Water level 3.9 m relative to CGVD28, if Hurricane Juan occurred today at HHWLT + conservative 100-year Sea Level Rise of 1m

- Scenario 3 (7.9m): Water level 7.9 m relative to CGVD28, if Hurricane Juan occurred today at HHWLT + extreme 100-year Sea Level Rise of 5 m

- Scenario 4 (15m): Water level 15.0 m relative to CGVD28, if Moderate Tsunami occurs

- Scenario 5 (30m): Water level 30.0 m relative to CGVD28, if Large Tsunami occurs

Three of the scenarios are related to the water level seen during Hurricane Juan, which made landfall in the HRM as a Category 2 hurricane on September 29, 2003 and produced a maximum recorded water level of 2.1 m CGVD28 (Lohr, 1970). Had Hurricane Juan occurred on HHWLT, the water level would have been 2.9 m CGVD28. If Hurricane Juan were to happen on HHWLT after a very conservative sea level rise of 1 m in 100 years, the water level would be 3.9 m CGVD28, and so on. The first three scenarios are selected for microsimulation modelling, as the peninsula becomes almost an island under the last two scenarios which might require an evacuation through airlift or an intervention by navy.

4.3.1.3 Flood Depth Analysis

The depth of water over the land for each of the flooding scenarios is determined by subtracting the flood water level surface from the DEM. The analysis of the results provides a depth value in each 2m pixel. Some areas anticipate extensive flooding over roads (>2 km inundated). Thus, reporting the exact depth of water over each meter of road would produce extensive results that would require further summarization and analysis. Therefore, it was determined that the water depth would be divided into six categories as below:

- Depth class 1: water depth ≤ 0.5m
- Depth class 2: 0.5m < water depth ≤ 1.0m
- Depth class 3: 1.0m < water depth ≤ 2.0m
- Depth class 4: 2.0m < water depth ≤ 5.0m
- Depth class 5: 5.0m < water depth ≤ 10.0m
- Depth class 6: water depth > 10.0m

4.3.1.4 Flood Risk Model Results

The developed GIS-based flood risk model simulates each flooding scenario considered in this study and predicts the following flooding extents as shown in **Figure 4-2**. The Halifax Peninsula has five exits as shown in **Figure 4-2**, such as (i) Exit 1: Bedford Highway, (ii) Exit 2: Highway 102, (iii) Exit 3: Armdale Rotary, (iv) Exit 4: Macdonald Bridge, and (v) Exit 5: Mackay Bridge.

Figure 4-2 Flooding extent in the Halifax Peninsula under (a) 2.9 m, (b) 3.9m, and (c) 7.9m flooding scenarios

The major street flooding is near exit 3 on Quinpool Road. The rotary (exit 3) is the most susceptible piece of road on the peninsula, with over 43% of the rotary impacted under 3.9 m flood scenario and over 88% impacted under 7.9 m flood scenario. In addition, Bedford Highway (exit 1) is also inundated by 47.8% of its total length in the 7.9 m flood scenario. The length of each road within the study area impacted by floods of different extremes is shown in **Table 4-1**. The affected links are identified on the Halifax maps in **Appendix A (Figure A4 – Figure A6)**.

Table 4-1 Identified Flooded Links based on the Flood Risk Model Results

Name of roads	Flood water level (m CGVD28)	Length of roads flooded (m)	Original length of roads (m)	% of roads impacted by flooding
Armdale Rotary	2.9	234.6	1324.3	17.7
	3.9	576.1		43.5
	7.9	1175.1		88.7
Barrington Street	2.9	0.0	7782.2	0.0
	3.9	162.4		2.1
	7.9	660.5		8.5
Bedford Highway	2.9	0.0	3974.6	0.0
	3.9	0.0		0.0
	7.9	1898.9		47.8
Chebucto Road	2.9	0.0	2201.2	0.0
	3.9	0.0		0.0
	7.9	79.0		3.6
Joseph Howe Drive	2.9	0.0	2873.3	0.0
	3.9	0.0		0.0
	7.9	149.2		5.2
Kearney Lake Road	2.9	0.0	269.4	0.0
	3.9	0.0		0.0
	7.9	110.2		40.9
Quinpool Road	2.9	245.4	2420.7	10.1
	3.9	398.4		16.5
	7.9	464.3		19.2

4.3.2 Dynamic Traffic Microsimulation Modelling

4.3.2.1 Network Model and Data Used

This study develops a microscopic traffic simulation model for Halifax. The traffic microsimulation modelling process follows four steps: (1) data processing, (2) network coding, (3) dynamic traffic assignment, and (4) calibration and validation of the model. Different data including, road geometry information from the Halifax Geodatabase 2012, travel demand data from the Halifax transport network model, and signal timing data from the HRM Public Work Traffic Study 2014 were used to develop the model. This study models at the finer level appropriately representing all essential traffic network modelling components that can be used in VISSIM. The Halifax transport network is built using open street map within VISSIM. The model can represent disaggregated network elements, including intersections, individual vehicle movement, driving behavior such as lane changes, acceleration, deceleration, traffic signals. It also can identify queue building and bottlenecks in the network. Hence, the model provides information for contrasting traffic operation scenarios.

In total, the coded network has 1,310 links and connectors, including, bridges, highways, rotary, and all arterial roads within the study area. 41 major and 12 stop sign-controlled intersections are coded in the network. All the intersections are modeled in greater details with actual traffic signal time and phase splits. A fixed signal timing plan obtained from the HRM traffic signal data is used to model the traffic signals. In this model, a signal controller is built for each of 41 intersections to regulate through and turning traffic flows at intersection. Each signal phase is defined by a signal group under a signal controller a shown in **Figure 4-3**.

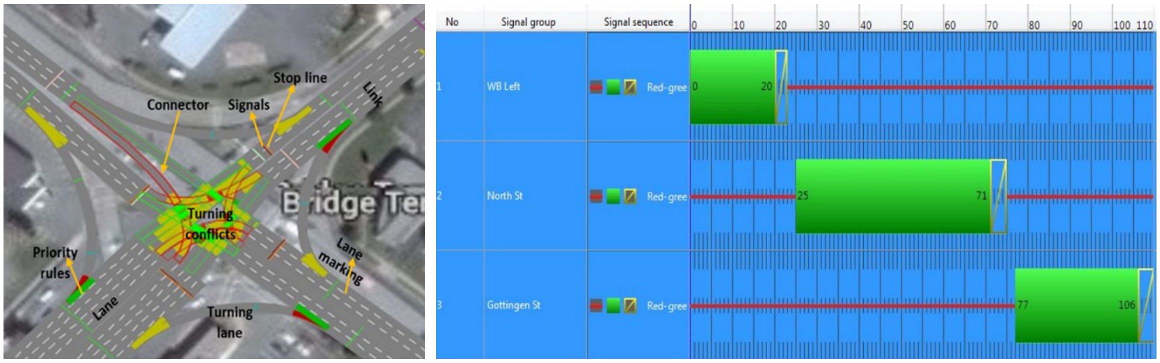


Figure 4-3 Elements of traffic microsimulation model developed for testing a mass evacuation of the Halifax Peninsula

The sequence e.g., red-green-amber and the split times obtained from traffic signal data are then included in the signal group. Signal controller controls the traffic entering the intersection; however, turning behavior is not regulated by the controller if not protected. To model the yielding behavior of the turning vehicles (left or right), conflicting areas are resolved, and priority rules are placed where necessary. This study resolves 1930 turning conflicts in the network where red color suggests the turning vehicles yield to vehicles from the opposite and/or transverse directions. Stop signs are implemented for the unsignalized intersections.

4.3.2.2 Dynamic Traffic Assignment

Vehicle trips are generated stochastically in the simulation using an average time gap between the entry of two successive vehicles in the network obtained from a Poisson distribution. The vehicle is then assigned a lane and a route based on the traffic congestion in the network ensuring less impacts on its desired speed and consequently travel times. A dynamic traffic assignment procedure is implemented to replicate a heavily congested transport network operation and capture driver's route choices in response to congestion. In this process, total simulation period is divided into smaller evaluation intervals to capture the changes in traffic conditions and subsequent changes in travel time. If a vehicle operates on a link/edge for more than one evaluation interval, still the model continues measuring the travel time for that vehicle, which manifests the actual heavily congested traffic condition in the network. The number of iterations required depends on the convergence criteria which are user defined. Travel time measured in the current iteration based on the following equation (PTV 6.0, 2014) will be used for path search in the next iteration.

$$T_i^{q,e} = \left(1 - \frac{1}{Q+q}\right) * T_i^{q-1,e} + \frac{1}{Q+q} * TC_i^{q,e} \tag{1}$$

where, Q measures the importance of measurements in the distant iteration, e, q, and i are the index of the evaluation interval, iteration, and edge respectively. $TC_i^{q,e}$ is the measured travel time at edge i in the evaluation interval e at current iteration q. $T_i^{q,e}$ is the smoothed travel time at edge i in evaluation interval e at current iteration q that will be used for path search in the next iteration. Best path is identified based on the cost which is a function of travel time that changes over the course of an iteration. Consequently, multiple best paths are produced during an iteration and used for the next iteration until the model is converged. A logit function is used to distribute the traffic across the best paths identified.

The microsimulation model developed in this study is extensively calibrated and validated. The business as usual (BAU) traffic flow from 0600 to 1000 is simulated for calibration and validation purposes where the simulation hour between 0600 - 0700 is used as warming period. The model is calibrated and validated for the hours between 0700 – 0900 using an advanced sampling method called 'Latin Hypercube'. Three driving behavior parameters are considered for calibration purposes. The observed traffic count data obtained from HRM is utilized for traffic volume-based validation purpose. This data was collected using Miovision cameras and the dataset contains traffic counts at one hundred and two locations. The details of calibration and validation of the model can be found in the following section.

4.3.2.3 Calibration of Driving Behavior Parameters

This study calibrates three car-following parameters of the Wiedemann 74 car-following model. The parameters include (i) parameter 1-average standstill distance (ax), (ii) parameter 2-additive part of safety distance (bx_add), and (iii) parameter 3-multiplicative part of safety distance (bx_mult) (Wiedemann, 1974; Olstam and Tapani, 2004). These three parameters together give a car-following distance according to the following equations (PTV 6.0, 2014).

$$d = ax + bx \tag{2}$$

where,

d is safety distance

ax is average standstill distance

bx adjusts time requirement values which can be written as:

$$bx = \left(bx\_add + bx\_mult * z\right) * \sqrt{v} \tag{3}$$

where, z is a value of range [0, 1], and normally distributed around 0.5 with a standard deviation of 0.15.

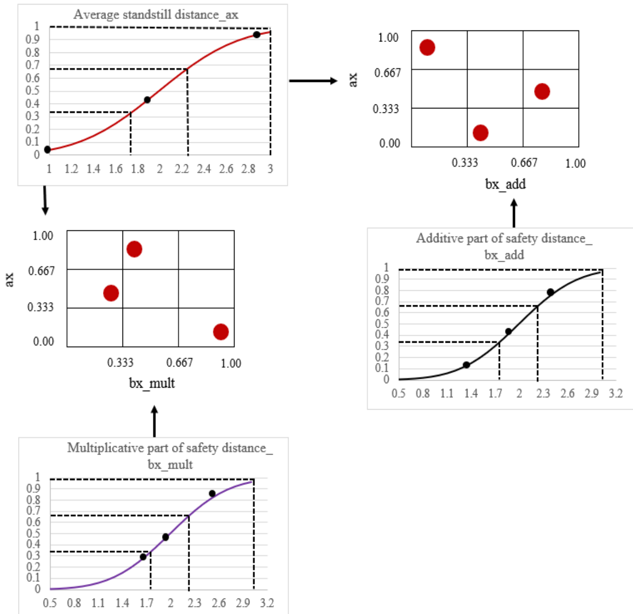
v is vehicle speed

Literature suggests that the range of the values of the parameters lie between 1-3m for ax (Park and Schneeberger, 2003), and 0-3 for bx_add and bx_mult used in Cobb Parkway model calibration (Miller, 2005). The combination of the values of the parameters plays an important role to replicate actual traffic flow in the simulator. Very often, the number of combinations of the parameters is so large that it is difficult to evaluate possible scenarios within the feasible time limit. If there are n variables, each having z number of subdivisions within its range, the total number of possible combinations is z^n. Supposing $n=4$ and $z=10$, it gives a very large combination number (10^4 = 10000) to evaluate. Therefore, this study uses a Latin Hypercube Sampling (LHS) technique to control the number of parameter combinations and to reduce the simulation time and cost. It refers to a statistical method in which the ranges of the values of n variables are subdivided into equally probable intervals, z. Next, sample points are selected from the interval to fill a Latin Square Grid, which contains pair variables along two axes and only one element in each row and each column (**Figure 4-4**). Thereby, the advantage of using this method is that it does not need more samples for more variables and the full range of the distribution can be sampled consistently. The LHS process is summarized below.

- Step 1: Stratify cumulative probability function of each variable into three equally probable sub-divisions

- Step 2: For each variable, a random sample is drawn from each stratum which ensures that samples more accurately reflect the distribution of the values in the input probability distribution. Thus, this method eliminates the insufficiency in Monte-Carlo simulation

- Step 3: For any pair, randomly selected values must come from different strata



$$\text{Combination set} = \begin{Bmatrix} ax\_avg & bx\_add & bx\_mult \\ 1.00 & 2.62 & 2.38 \\ 1.00 & 1.85 & 1.83 \\ 1.00 & 2.62 & 0.70 \\ 1.00 & 0.60 & 0.70 \\ 1.00 & 0.60 & 2.38 \\ 1.88 & 0.60 & 2.38 \\ 1.88 & 1.85 & 1.83 \\ 1.88 & 0.60 & 0.70 \\ 1.88 & 2.62 & 0.70 \\ 1.88 & 2.62 & 2.38 \\ 2.62 & 0.60 & 0.70 \\ 2.62 & 0.60 & 2.38 \\ 2.62 & 1.85 & 1.83 \end{Bmatrix}$$

Figure 4-4 LH process to generate combination sets of driving behaviour parameters

The LHS process has identified 13 parameter combinations as shown in **Figure 4-4**. Each combination is considered for simulation. The goodness-of-fit of the model is measured in terms of R^2 value which quantifies the closeness between the simulated and observed traffic count. The combination, which gives a value 1 for ax, 0.6 for bx_add, and 0.7 for bx_mult exhibits better network performance compared to other combinations in terms of R^2 value. The study performs route choice parameter calibration for further improvement of the traffic flow in the simulator.

4.3.2.4 Route Choice Parameter Calibration

For further improvement of the traffic flow at a few local network links, route choices are calibrated in the simulator. Route choice calibration is conducted by adding link surcharges (i.e., cost components) to modify assignment results. Links that attract more traffic volume than observed can be assigned a positive surcharge, thus reducing their desirability. In the absence of well-defined guidelines on the relationship between the surcharge value and traffic divergence, a surcharge value of 30 is considered as the starting value based on experience. Through several iterations, surcharge value 50 for 6 links, 100 for 7 links, 150 for 2 links, 200 for 6 links, and 500 for 3 links have been imposed. Improvement is identified by comparing the simulated traffic flow with the observed traffic count at these links.

4.3.2.5 Validation of Microsimulation Model

This study has conducted a traffic volume-based validation using traffic count data obtained from the multiple data sources as mentioned earlier. The exit points and several nearby intermediate intersections totaling 21 locations are validated in terms of minimum deviation between the observed and simulated traffic counts. The goodness-of-fit of the model is evaluated by determining R^2 for the hours of 0700-0800 and 0800-0900. The validation results in **Figure 4-5** suggest R^2 values of (a) 82% and (b) 84% respectively for these two hours.

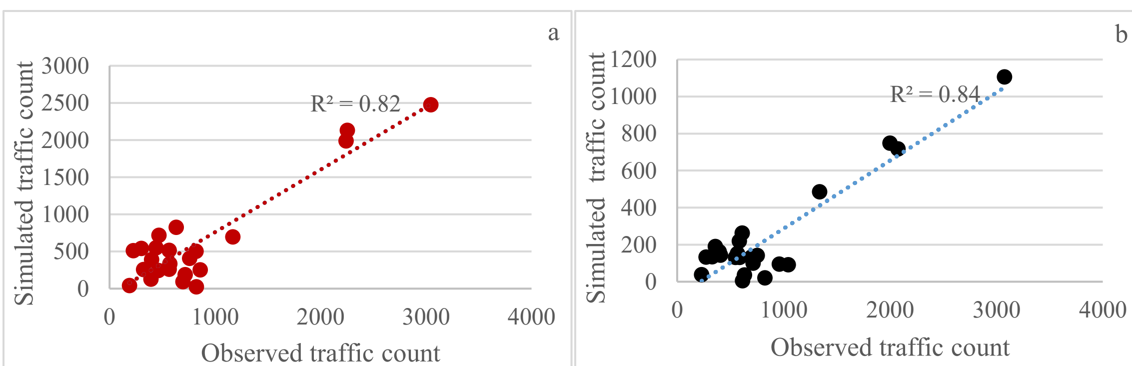


Figure 4-5 Validation of microsimulation model for (a) 0700-0800 and (b) 0800 – 0900

4.3.3 Evacuation Cases for Microsimulation Model

This study follows a curb-side simulation approach to evacuate a demand of 34,808 vehicles from the Peninsula. The demand is estimated for the period of 0600 – 1000 using the Halifax transport network model following a simple four-stage travel demand calculation method. The time 0900 – 1000 is considered as the ending hour of the morning peak period in Halifax. The head count is maximum at 1000 representing the highest demand in this region and it is considered as the starting time of evacuation in this study. The study also assumes that it is a mandatory evacuation, and every resident will evacuate upon the evacuation order is issued. This study selects two shelters due to their sufficient accommodation capacity and safe distance from the Halifax Peninsula. The shelters include (i) Shelter 1- Charles P. Allen High School, and (ii) Shelter 2- Nova Scotia Community College (NSCC), Akerley campus (**Figure 4-2**). It is evident that not all evacuees would choose shelters as their destinations. Therefor, this study assumes that 20% of the total evacuees will take other shelters, for instance, the homes of relatives and friends. The rest can be accommodated within the selected shelters. In total, four evacuation cases are considered within the simulation model.

- Case 1 (No links flooded): No links are affected by any flood scenario
- Case 2 (2.9 m): 0.11% links of the modelled network are affected
- Case 3 (3.9 m): 0.27% links of the modelled network are affected
- Case 4 (7.9 m): 1.1% links of the modelled network are affected

4.4 Results and Discussion

4.4.1 Overall Evacuation Results

Table 4-2 presents overall evacuation results for all evacuation cases tested within the traffic microsimulation model. The results from evacuation case 4 (7.9m) suggest that the available vehicle paths from the origin zones to the shelter locations are disrupted by 31.2% relative to evacuation case 1 (no links flooded). The more severe the flood-related network damages, the fewer the alternative routes would be left for evacuees. The results suggest that the capacity of the Halifax Peninsula transport network is limited to accommodate for the entire evacuation demand in the network if flood water level is 7.9 m (case 4) and above unless countermeasures are applied. Only 83% of evacuees can be admitted into the network and evacuated within 15 hours from the beginning of the evacuation under this flooding condition. Traffic congestion in the network is already at peak when even 17% of evacuees are not in the network in this case. A prioritizing and staged evacuation strategy could help to evacuate all evacuees under this circumstance. In the case of flood scenarios that demonstrate a lower rise in water level (2.9m and 3.9 m), almost all the evacuees can be evacuated within an evacuation time equal to or less than 15 hours.

Table 4-2 Overall Evacuation Results for the Halifax Peninsula

Scenarios	Case 1: No links flooded	Case 2: 2.9 m	Case 3: 3.9 m	Case 4: 7.9 m
Loss of Connectivity, %	0.0	23.3	23.7	31.2
Total Departure, %	100	100	100	83
Completed Evacuation, %	100	100	100	83
Evacuation Time, hr.	11	13	15	15
Increment in evacuation time w.r.t case 1, hr.	-	2	4	4

Furthermore, once the fully developed Halifax regional transport network model (Bela and Habib, 2018) becomes available, the study has updated the estimation process to obtain the highest evacuation demand, which is calculated as 65,000 vehicles. The evacuation cases are re-evaluated within an updated traffic simulation model in accordance with new demand and updated zoning system of the regional model. The modified evacuation results are presented in **Table 4-3**. This chapter analyzes the congestions for initial demand while the following chapters utilizes the results in relation to the updated highest demand for comparing with other evacuation scenario outcomes. Clearance time across Halifax Peninsula zones for all flood scenarios are visualized in **Appendix B (Figure B1 – Figure B4)**.

Table 4-3 Halifax Peninsula Evacuation Results for the Highest Demand

Scenarios	Case 1: No links flooded	Case 2: 2.9 m	Case 3: 3.9 m	Case 4: 7.9 m
Loss of Connectivity, %	0.0	23.3	23.7	31.2
Total Departure, %	100	100	100	87
Completed Evacuation, %	100	100	100	87
Evacuation Time, hr.	22	22	23	23
Increment in evacuation time w.r.t case 1, hr.	-	0	1	1

4.4.2 Evacuation Completion Pattern

Figure 4-6 presents (a) cumulative percent arrival, and (b) the hourly arrival of evacuees at shelters for all the evacuation cases considered in this study. The results in **Figure 4-6a** suggest that to complete a 50% evacuation it takes 5.5 hours to 7.5 hours with the increase in water level by 2.9m in case 2 to 7.9m in case 4. In the case of a 7.9m flood scenario (case 4), the evacuees are distributed over 15 hours as the network has limited discharge capacity from the beginning of the evacuation due to flooding of the key links in the network. It can be concluded that the arrival rate of evacuees at shelters is uniform when the network has fewer route options. In case 2 (2.9m), part of Armdale Rotary (exit 3) on the west of the Halifax Peninsula (**Figure 4-2**) is affected. It interrupts traffic operations of several routes from the peninsula to shelter 1. The network disruption spreads to the east in case 3 (3.9m). During the flood of 7.9 m water level (case 4), Bedford Highway (exit 1) located on the west of the peninsula is also added to the list of the flooded links. The scenario presents a transport network that is immensely disrupted which ultimately causes an incomplete evacuation of the Halifax Peninsula. **Figure 4-7** presents the visualization of the traffic flows and congestion spillback during the evacuation under a 7.9m flood scenario. Exit 1 and 3 are completely flooded in this scenario. Further traffic flow visualization, travel times and traffic congestion measurements for all scenarios can be found in **Appendix C**.

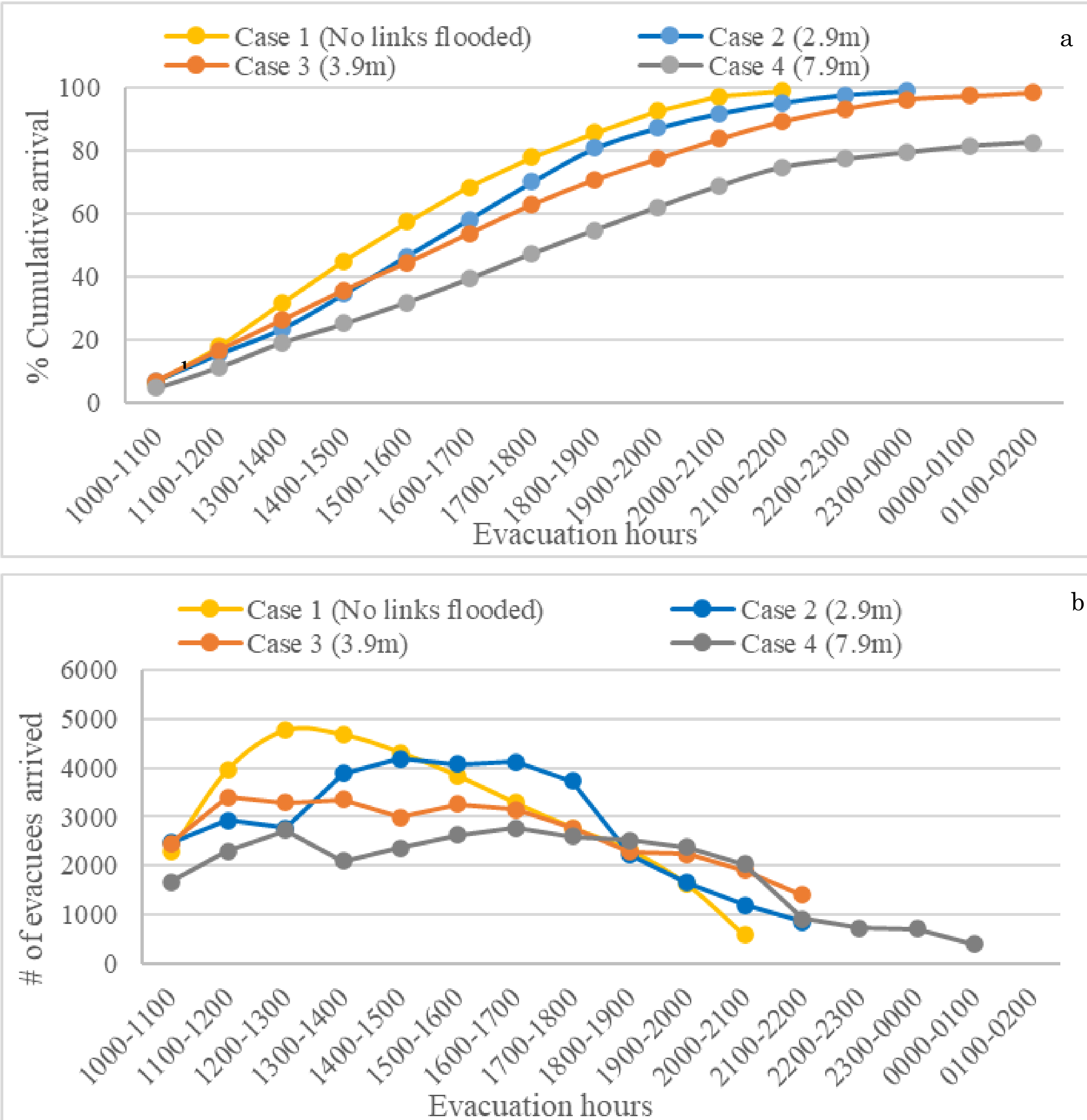


Figure 4-6 (a) Cumulative percent arrival and (b) hourly arrival of evacuees at shelters under different flood scenarios

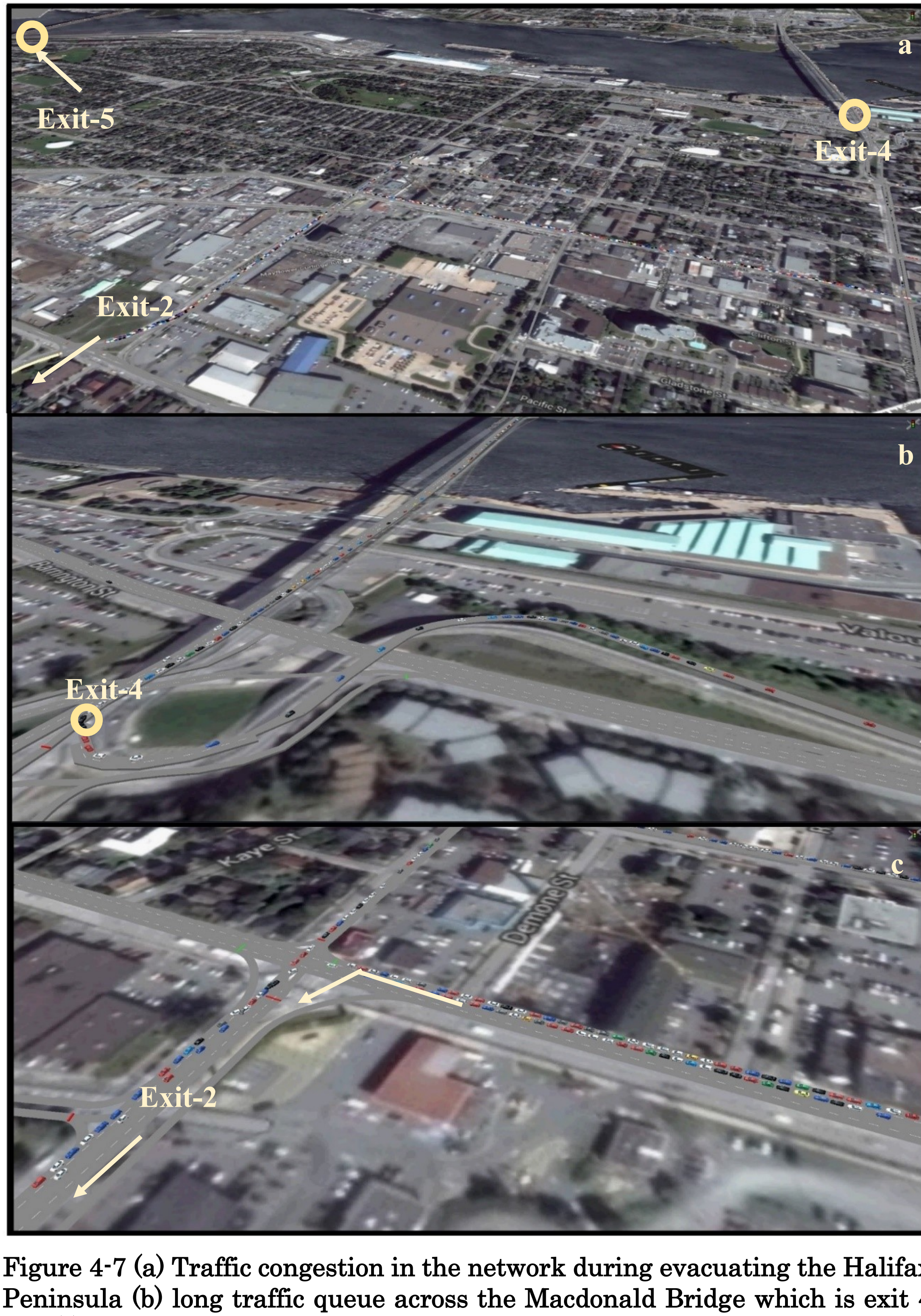


Figure 4-7 (a) Traffic congestion in the network during evacuating the Halifax Peninsula (b) long traffic queue across the Macdonald Bridge which is exit 4 and (c) traffic congestion due to traffic flow on major arterial roads approaching exit 2

4.4.3 Network Congestion

4.4.3.1 Vehicle Density and Average Speed

This study also examines the average speed and number of vehicles present in the network for each evacuation case. Flood-related damages to network links causes an increased number of vehicles to stay in the network. **Figure 4-8** shows that the number of vehicles in the network remains high over a longer duration in case 4 (7.9m) since there are fewer alternative evacuation paths. However, the congestion level in terms of number of vehicles in the network in different evacuation cases depends on the arrival rate of evacuees to the destinations. For example, the number of vehicles in the network varies in the range of 8,000 - 13,000 from case 1 to case 4. As indicated earlier, case 4 has the lowest arrival rate, the number of vehicles in the network has peaked at 13,000 in this case. These vehicles create congested traffic conditions and thereby reduce the average speed in the network.

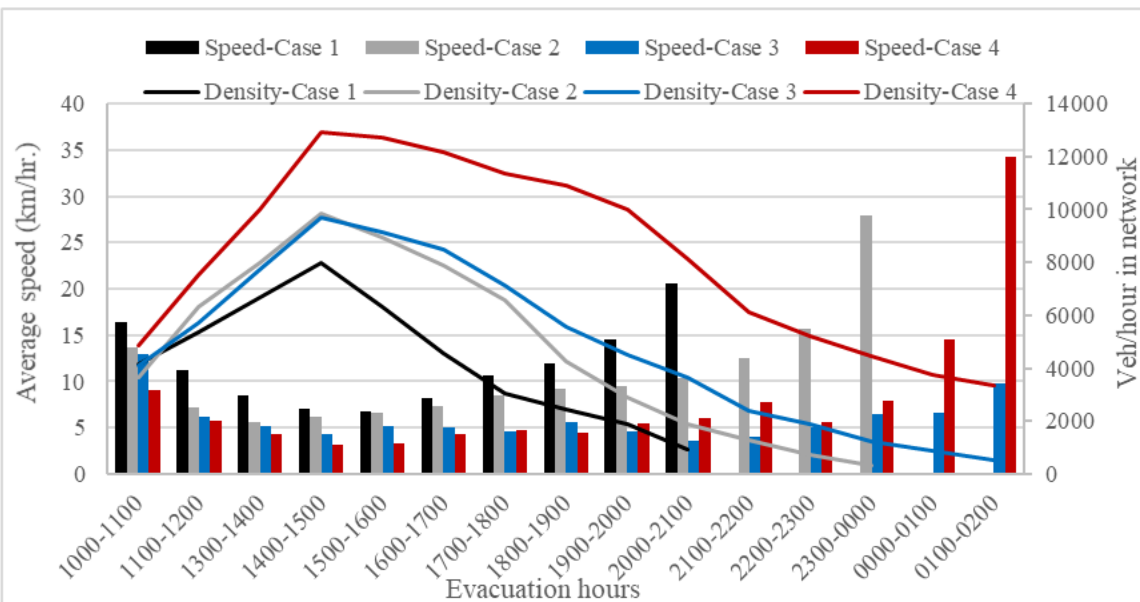


Figure 4-8 Vehicle density and average speed profile for the evacuation of the Halifax Peninsula under different flooding scenarios

4.4.3.2 Traffic Flow Indicators

Table 4-4 presents an in-depth evaluation of the network performance in all evacuation cases tested for the Halifax Peninsula. The traffic analysis results are tabulated for each of the four evacuation cases at one-hour interval within the respective entire evacuation times. Delays per vehicle increase with the increase in flood water level from case 2 to case 4 as does the total delay time. Initially, in each case, delay increases rapidly and reaches a maximum within 4-7 hours from the beginning of the evacuation. The results indicate that vehicles accumulate and create congested traffic conditions in the network. The values of different criteria included in **Table 4-4** also suggest a sustained congestion from 4th to 7th hour of the evacuation. Although evacuation case 3 and 4 show similar level of traffic congestion, 100% of the evacuees are moved to safe locations in case 3 against the 83% in case 4. The total distance travelled is the lowest in case 4 as only 83% of evacuees complete trips from the peninsula to shelters.

Table 4-4 Hourly Network Performance during Evacuation of the Halifax Peninsula

Case	Criteria	1st hour	2nd hour	3rd hour	4rth hour	5th hour	6th hour	7th hour	8th hour	9th hour	10th hour	11th hour	12th hour	13th hour	14th hour	15th hour
Case-1 (No-links flooded)	Avg. delay per vehicle	17.79	22.70	25.81	32.14	33.85	27.91	22.64	14.64	11.55	17.41	13.87				
	Avg. number of stops per vehicle	117.4	94.1	80.9	89.1	93.1	98.8	117.4	120.3	140.9	203.3	149.1				
	Total delay time	2382.78	4014.22	5151.85	6743.69	6258.01	4469.65	2720.20	1097.88	446.87	393.50	187.27				
	Total travel time	3871.75	5685.24	6886.53	8245.07	7907.34	6203.40	4258.53	2177.23	945.17	669.97	435.32				
	Total distance travelled	65933.3	74293.0	77201.8	66800.8	72596.7	74912.0	66214.6	46022.1	21782.9	12213.8	10968.4				
	Delay stops avg.	11.98	18.43	21.97	28.19	29.51	23.09	17.38	9.83	6.55	10.31	8.26				
Case-2 (2.9 m)	Avg. delay per vehicle	20.27	29.94	35.09	36.01	37.17	35.79	33.47	31.83	32.67	29.11	27.06	20.06	8.18		
	Avg. number of stops per vehicle	107.8	105.7	61.5	72.9	75.4	74.7	76.9	79.5	108.3	140.3	193.0	170.0	71.8		
	Total delay time	2418.71	5010.94	6950.63	8547.55	8403.50	7396.99	6103.95	4221.44	2702.76	1647.89	1007.10	422.67	54.78		
	Total travel time	3489.31	5972.21	7956.98	9905.80	9880.28	8865.92	7584.86	5370.36	3480.34	2177.49	1429.75	660.09	150.12		
	Total distance travelled	47438.7	43043.0	44780.6	60673.2	65781.2	64925.2	64847.3	49621.7	32911.8	22411.2	17911.7	10330.6	4201.9		
	Delay stops avg.	15.18	25.71	32.37	32.92	33.72	32.24	29.74	28.52	28.44	24.05	20.12	14.20	5.15		
Case-3 (3.9 m)	Avg. delay per vehicle	21.23	32.29	35.95	40.23	41.19	41.15	41.98	40.37	43.68	46.31	45.75	43.12	40.87	40.80	29.70
	Avg. number of stops per vehicle	71.15	60.79	64.24	64.01	75.61	74.64	72.62	73.43	73.02	60.60	83.70	101.99	101.70	94.03	77.69
	Total delay time	2581.84	4990.67	7205.36	9323.51	9363.47	8523.52	7900.22	7298.95	6183.01	4814.80	3978.87	3162.50	2235.51	1434.21	664.79
	Total travel time	3697.02	5831.13	8178.67	10352.28	10617.22	9657.15	8839.48	8401.02	6944.08	5261.69	4406.77	3609.78	2653.01	1711.65	874.33
	Total distance travelled	47817.3	36363.8	42156.9	44338.6	54437.7	49016.6	40331.9	47034.5	32380.4	18904.6	17768.2	18388.7	17032.6	11400.5	8531.4
	Delay stops avg.	17.23	29.46	33.35	37.70	38.07	38.04	39.10	36.95	40.68	44.17	42.81	39.71	37.44	37.65	26.93
Case-4 (7.9 m)	Avg. delay per vehicle	25.49	34.69	39.14	45.10	47.09	44.46	42.32	43.65	40.76	42.37	37.53	42.26	39.40	26.24	2.72
	Avg. number of stops per vehicle	122.6	96.2	65.3	54.2	67.4	86.3	101.1	66.3	100.7	86.2	37.5	35.6	52.3	93.6	24.6
	Total delay time	3147.99	6158.10	8275.63	10032.45	9898.87	8971.30	8142.71	7458.32	6397.76	5062.32	2996.80	1942.01	1204.39	484.15	18.05
	Total travel time	3955.89	7076.69	9159.57	10783.18	10694.39	9923.45	9119.81	8309.69	7319.49	5881.02	3662.42	2236.51	1481.46	750.80	118.74
	Total distance travelled	35634.0	40869.6	39524.7	33746.0	35573.3	42131.9	43541.1	37281.0	40301.7	35435.6	28475.8	12587.7	11626.5	10930.5	4064.9
	Delay stops avg.	20.05	30.62	36.37	42.89	44.47	41.14	38.16	40.90	37.02	39.08	35.43	40.16	36.35	21.08	1.46

4.5 Conclusions

This chapter presented a dynamic traffic microsimulation modelling of a mass evacuation of the Halifax Peninsula considering floods of different water levels informed by a GIS-based flood risk model. The combined digital elevation and dynamic traffic assignment-based microsimulation modelling techniques are used to evaluate flood related damages to the network and the subsequent interruptions to evacuation traffic flows.

The simulation results suggest that it would take 15 hours to evacuate 100% of evacuees from the peninsula with a flood water level of 3.9m. A flood of water level of 7.9m reduces evacuation paths from the peninsula to shelters by 31.2%. It creates a bottleneck traffic condition which allows only 83% of evacuees to reach shelters, against the 100% in case of 3.9m. The simulation results show that traffic accumulates increasingly as the evacuation time progresses, and flood water level rises in different evacuation cases. The number of vehicles peaks at 13,000 in case of 7.9m flood, indicating that the arrival rate of the evacuees is much lower than that of the other flood scenarios. Traffic congestion is found to peak within 4-7 hours from the beginning of the evacuation.

This research contributes to the literature by developing a city-scale DTA-based evacuation microsimulation model that considers traffic flow interruptions informed by a flood risk model. The study asserts that only auto-based evacuation may require a longer evacuation times if no countermeasure is applied. For instance, 17% of residents could not be evacuated due to serious traffic congestion and network disruptions under an extreme flood risk scenario in Halifax. In addition, the model does not consider other types of risks and complexities, such as traffic disruptions, and the vulnerabilities that people are exposed to in assessing evacuation scenarios. Furthermore, evacuating all citizens at once could take a longer time since spillback could gridlock the narrow roads of historical towns. The following chapters develop multiple modules and strategies to address further complexities, and to regulate traffic demand and congestion in the network during an evacuation. Such modular-based evacuation modelling tool will help emergency professionals, engineers, and planners to understand uncertainty, and risks associated with a mass evacuation and tackle multi-layer challenges in an efficient manner.

Chapter 5

Multimodal Evacuation[2]

5.1 Introduction

This chapter develops a multimodal traffic evacuation microsimulation model to explore how to evacuate all citizens, including public transit dependent populations, from an area affected by a natural or manmade disaster. It is difficult to observe disaster-related evacuation events and consequently, many coastal cities lack comprehensive multimodal models for evacuation planning (Clarke and Habib, 2012). The existing evacuation plans primarily focus on auto-based evacuation (Renne et al., 2011). However, it is also imperative to utilize transit systems during an evacuation to meet the transportation needs of the transit-dependent group. A special Transportation Research Board (TRB) committee produced a report entitled "The Role of Transit in Emergency Evacuation" explaining how transit can play a critical role in emergency evacuation (TRB, 2008). The committee reviewed the literature and examined emergency responses and evacuation plans of the 38 largest urban areas in the United States. The study asserted that it is a major concern that transit has not been included in evacuation plans. Notably, the New Orleans evacuation is an example of the importance of effective evacuation planning for transit-dependent groups. In 2005, Hurricane Katrina hit New Orleans, and 36% of the population did not evacuate for the sole reason of not having a car (Renne et al., 2011). Another example exists in 2005 during Hurricane Rita, where

[2] This chapter is largely derived from the following peer-reviewed journal paper:

- Alam, M. J., Habib, M. A., and Venkatadri, U. (2019). Development of a Multimodal Microsimulation-Based Evacuation Model. *Transportation Research Record*, 2673 (10), 477-488 there were limited plans to evacuate the transit-dependent population along the Gulf Coast of the U.S. In this scenario, public transportation and school buses were not readily available, and the city declared ten pickup locations in an ad-hoc fashion having no prior evaluation of the needs for transit demand (Litman, 2006). Therefore, to adequately evacuate all citizens of an area, the transportation needs of transit-dependent groups should be taken into consideration. Although the elevated risk experienced by transit-dependent populations are well identified and realized (Renne et al., 2011; Litman, 2006; Wolshon et al., 2005), deficiencies still exist in public transportation planning for emergency evacuation (Hess, 2006; Hess and Gotham, 2007). In the absence of multimodal transportation modelling, transit systems may not be able to support emergency mass evacuations (Litman, 2006). Accordingly, transit agencies need to establish pick-up locations and transit routes proactively and develop plans for resource allocation. In summary, there are a limited number of studies on transit evacuation planning, but a clear gap exists in the literature. Unaddressed topics include the determination of emergency pick-up locations, also known as 'marshal point' locations, transit evacuation routes and an exploration of network conditions with multimodal evacuation plans. This chapter addresses the deficiency in the existing traffic evacuation modelling by incorporating planning decision components (e.g., marshal point location and transit route choice decisions) within the evacuation microsimulation modelling framework to evaluate a multimodal evacuation plan.

Therefore, the objectives of this chapter are to (i) develop an optimization model to determine marshal point locations and transit routes while addressing evacuation transit demand, and (ii) incorporate marshal point locations and transit route component within a microsimulation model for testing and evaluation of a multimodal evacuation operation. Transit demand and bus stops for multimodal evacuation are obtained from a Halifax transport network model and Halifax Geodatabase, respectively (**Appendix D**). A Mixed Integer Linear Programming (MILP) technique is used to formulate the marshal point location and transit route choice problems. A novel solution approach using the "Branch and Cut" algorithm is implemented to determine marshal point locations and transit routes. The study has demonstrated the effects of Branch and Cut strategy on the optimization computation time. The method improves runtime and quality of solutions compared to traditional methods.

5.2 Literature Review

Evacuation research has recently evolved in the area of traffic operation management to evaluate hypothetical evacuation scenarios during an emergency and to develop evacuation plans and policies. The evacuation scenarios in several studies are evaluated using traffic simulation models, which have recently grown as a powerful tool for forecasting traffic flows. Specifically, they are advantageous for developing and comparing contrasting evacuation plans under different emergency conditions and providing insights into traffic congestion and bottlenecks during the evacuation. Many studies mentioned earlier developed traffic simulation models for testing and evaluation of different evacuation scenarios. Chapter 4, which is partially adopted from Alam et al. (2018), developed a traffic evacuation microsimulation model. The study suggested that it would require 15 hours to evacuate the Halifax Peninsula by auto. Zhang et al. (2013) developed a mesoscopic traffic simulation model in TRANSIM to test evacuation performance in the Gulf Coast road network under six evacuation scenarios. **Table 5-1** includes a brief review of studies on evacuation planning and modelling. It illustrates the breadth of the evacuation studies using different methods including optimization, macro, micro and agent-based simulation modelling. Moreover, it categorizes the studies based on the utilization of different modes in evacuation. Most of these studies focus on auto-based evacuation, which has motivated this study to develop a multimodal traffic evacuation microsimulation model to assist transit-dependent citizens in an emergency evacuation.

The importance of public transportation in an emergency evacuation has been highlighted since Hurricane Katrina and Hurricane Rita in the U.S. There are limited studies on multimodal and/or transit-based evacuation modelling. Naghawi and Wolshon (2011) utilized a multimodal evacuation simulation model to evaluate different network loading scenarios for an evacuation. The study considered seventeen pick-up locations to evacuate the carless population using six bus corridors. The study concluded that average delays and queue length increased on interstate evacuation routes. Yang et al. (2018) developed a microsimulation-based multimodal evacuation model following linear programming to evaluate evacuees' waiting time taking into consideration of the cooperative behavior of evacuees. However, the establishment of transit demand-sensitive marshal point locations and evacuation routes for a multimodal evacuation is of paramount importance for better understanding the critical role of transit in an emergency evacuation.

In relation to identifying marshal point locations and transit routes, several studies (Kaisar and Parr, 2012; Wang et al., 2014) utilized optimization techniques, such as local search technique, linear, integer and mixed integer linear programing. A study (Abdelgawad and Abdulhai, 2012) utilized a "Branch and Price" algorithm in solving an integer programming (IP) problem to determine pick-up locations for a small-scale network of 500m radius and fourteen bus stops under a hypothetical evacuation scenario. Kulshrestha et. al. (2014) utilized a 'cutting plane' scheme to identify pick-up points for a network of twenty-two nodes. Kaisar et. al. (2012) developed a linear programming (LP) model to determine pick-up locations; however, mixed integer linear programming (MILP) is more effective, particularly, when one or more decision variables are restricted to integer solution space. Another study (Albert, 1999) suggested that “Branch and Bound” is an efficient and reliable algorithm to solve MILP problem. However, the disadvantages of these algorithms are that they are slow and/or unreliable. For example, a cutting plane scheme is unreliable, while the branch and bound algorithm is slow (Albert, 1999). Therefore, this study adopts a novel approach that combines “Branch and Bound” and “Cutting Plane Scheme” to solve the proposed MILP-based optimization problem regarding marshal point locations and transit routes. The combined solution approach is named the “Branch and Cut” algorithm.

The resulting transit marshal points and routes are utilized to develop a multimodal evacuation microsimulation model. The microsimulation model simulates a multimodal evacuation of the Halifax Peninsula and analyzes the evacuation performance in terms of clearance time, hourly percent evacuation, and traffic congestions. Evacuation performance by both auto and transit are compared and evaluated for developing policy recommendations.

Table 5-1 A List of Studies on Auto-based, and Multimodal Evacuation Modelling

Authors	Methods	Location	Evacuation type	Findings
Li et al. (2012b)	Dynamic traffic assignment within DYNASMART-P	Greater Jackson area as destination for an evacuation of New Orleans	Auto based	ITS strategy could increase existing highway capacity by 20%. Contraflow plus ITS strategy could increase evacuation capacity from 38% to 79%
Zou et al. (2005)	Optimization modelling and microscopic traffic simulation modelling within CORSIM	Ocean City, Maryland	Auto based	Six new evacuation plans are compared within an emergency evacuation system
Kaisar and Parr (2012)	Microscopic traffic simulation modelling within AIMSUN	Evacuation of twenty-two zones of Baltimore Downtown	Auto based	Comparison of different evacuation improvement strategies. Contraflow nearly doubles the evacuation capacity
Church and Sexton (2002)	Traffic simulation modelling utilizing PARAMICS	Mission Canyon community evacuation due to wildfire	Auto based	Recommendations such as using only the vehicle that is needed, elevate awareness and educate citizens using the simulation model
Shao et al. (2008)	Traffic microsimulation modelling within VISSIM	Beijing National Stadium Parking lot	Auto based	Total clearance time is found as 27 minutes
Wang et al. (2014)	Dynamic traffic assignment within DynusT	17.3 km^2 of Jackson Downtown	Auto based	Three hours required to evacuate 55,281 evacuees. Vehicle message sign is a promising strategy to improve evacuation performance. Contraflow should be carefully used for low demand

Authors	Methods	Location	Evacuation type	Findings
Abdelgawad and Abdulhai (2012)	Constraint programing approach	A no notice evacuation of City of Toronto	Transit based	TTC fleet can evacuate all transit-dependent population in 2 hours on average. Four subway lines of the City of Toronto can evacuate all subway riders in 154 min on average
Sayyady and Eksoglu (2010)	Mixed integer linear programming and mesoscopic traffic simulation modelling within DYNASMART-P	No notice evacuation of an area of 1-mile radius	Transit based	CPLEX is found time intensive compared to Tabu search and the model offers minimized casualties, and evacuation time
Abdelgawad and Abdulhai (2010)	Optimal Spatio-Temporal evacuation modelling and MDTCPD-VRP. Mesoscopic traffic simulation modelling within DynusT	City of Toronto	Multimodal	On average auto clearance time is 2 hours and net clearance time is 8 hours. Average transit-based evacuation time for TTC fleet is on average 2 hours.
Naghawi and Wolshon (2011)	Traffic microsimulation modelling within TRANSIMS	Southeastern Louisiana including Orleans and Jefferson Parishes	Multimodal	Traffic impact analysis for a multimodal evacuation operation with given network loading and transit scenarios
Yuan and Puchalsky (2015)	Dynamic User Equilibrium assignment within VISUM	Philadelphia, Pennsylvania	Multimodal	Evaluates scenarios regarding changing demand and traffic control conditions and offers insights into planning questions including evacuation time, the effects of transit on evacuation
Wang et al. (2016)	Near-field tsunami evacuation modelling using agent-based programing in NetLogo	Seaside, Oregon	Multimodal evacuation by car and walk	Mainly presents the impacts of variation in evacuees' decision making, including decision making time and mode choice on the coastal community life safety, i.e., mortality rate

5.3 The Context and Problem Statement

Halifax, the capital of Nova Scotia, is a city with narrow roads and limited exit/entry points. There is considerable marine movement through the Halifax Harbor, located alongside the Peninsula. Furthermore, Halifax is on a hurricane path that has previously caused devastation, as demonstrated in previous chapter and Alam et al. (2018). In 2003, Hurricane Juan made landfall in the Halifax Regional Municipality, causing eight fatalities. Just five months after Hurricane Juan, a winter storm nicknamed White Juan caused heavy snowfall in Halifax. Therefore, the Halifax Peninsula is a suitable candidate for empirical application of the proposed multimodal evacuation microsimulation model. This study considers a scenario in which residents of the Halifax Peninsula need to evacuate upon a mandatory evacuation order during emergency conditions. In response to the evacuation order, residents who own cars can evacuate themselves, while transit-dependent residents require assistance to move to safe locations. In the case of transit users, when the evacuation order is released, it is assumed that transit-dependent people from different zones (traffic analysis zones in this case) will gather at specified pick-up locations. Transit buses will be allocated to pick up evacuees waiting at pick-up locations and transport them to the shelters. The current Halifax evacuation plan considers almost all the existing bus stops as pick-up locations. Therefore, marshal point locations and transit evacuation routes need to be established prior to commencing multimodal evacuation. This study develops an optimization model to determine the marshal point locations and transit routes to evacuate transit-dependent population with a minimum time. The study does not consider the times or delays required by the evacuees to arrive at the marshal point locations. The planning decisions regarding marshal point locations and transit routes are then incorporated into the traffic microsimulation model to test the multimodal evacuation plan.

5.4 Methodology

5.4.1 Optimization Modelling Approach

To ascertain emergency transit marshal point locations and routes, this study uses a two-phase method to determine evacuation transit network: (i) marshal point location determination, and (ii) bus route determination. The proposed optimization model determines marshal point locations based on transit demand obtained from the Halifax regional transport network model (Bela and Habib, 2018). It minimizes the total walking distance from zone to marshal points. Data for walking distance from zones to bus stops is obtained from the 2012 Halifax Geodatabase. Buses are allocated to the transit routes following the Halifax transit schedule within the microsimulation model. A bus can serve multiple marshal points until it has reached its capacity. This study uses multiple depots to dispatch buses. It is assumed that all buses are gathered in the depots before dispatch. All transit routes start from any of the depots and are extended to the shelters. As a transit route contains multiple marshal points, a bus can keep serving evacuees until it reaches its capacity. Transit evacuation routes are chosen such that all marshal points are contained within the routes and total travel time is minimized.

5.4.1.1 Optimization Model for Marshal Point Location

Let $z \in Z$ denote a TAZ, where $Z = \{1,2,3....N\}$ is the set of all TAZs, and let $s \in S$ represent a bus stop, where $S = \{1,2,3....N\}$ is the set of all bus stops. A binary variable y_{zs} is used to make the marshal point location choice decision, where it takes '1' if a bus stop s is selected as the marshal point for zone z and '0' otherwise. Bus stops located within a threshold walking distance $d_{threshold}$ of TAZs are considered for selection through the optimization process. Each stop has a capacity of q_s. q_s has significant contribution in determining the minimum number of marshal point locations. This parameter is determined through an iterative process using different values for the bus stop capacity while satisfying distance criteria and evacuating all evacuees from TAZs. An overall capacity value for bus stop that yields the minimum number of marshal points is accepted. A variable x_{zs} is used to determine the share of the total demand at a TAZ, z that approaches bus stop s if s is selected as the marshal point for z. The transit demand of TAZ, z is denoted D_z. Based on the definition of the variables, the optimization model in this study follows a Mixed Integer Linear Programming (MILP) approach as the zone to bus stop demand variable is restricted to integer solution space. Following the descriptions and notations, the MILP-based optimization model of marshal point location choice decision is developed such that overall walking distance is minimized during an evacuation. The model formulation and the solution approach are described as follows.

Objectives:

$$Minimize \sum_{z\in Z}\sum_{s\in S} y_{zs} * d_{zs} \tag{1}$$

Subjected to:

i. $y_{zs} * d_{zs} \le d_{threshold}, \forall z, s$

ii. $\sum_{s\in S} x_{zs} \ge D_z, \forall z$

iii. $\sum_{z\in Z} x_{zs} \le q_s, \forall s$

iv. $x_{zs} \le y_{zs} * M, \forall\, z, \mathrm{s}$

v. $x_{zs} \geq 0, \forall\ z, s$

vi. $y_{zs} = \{0,1\}$

Constraint (i) ensures that walking distance from a centroid of a TAZ to a marshal point does not exceed a maximum threshold, constraint (ii) requires that all the residents in a zone must evacuate, constraint (iii) ensures that the capacity of a marshal point is respected, constraint (iv) ensures that no flow can be assigned to a stop if it is not selected as a marshal point, where M is a large number, constraint (v) and constraint (vi) describe decision variables as positive integer and binary.

The proposed "Branch and Cut" algorithm is implemented within the MPL Gurobi solver platform. This study utilizes "Branch and Cut" algorithm in MPL with all the conservative Gurobi cuts enabled. The cuts include Clique, Cover, GUB, MIR, Mod-K, and Network cuts, implied bound cuts, flow cover and path cuts, MIP separation and sub-MIP cuts, and zero-half cuts. Advantages of the proposed solution approach includes that it (i) improves constraint propagation and reduces the search space, and (ii) reduces the number of nodes by improving relaxation bounds. This optimization model provides marshal point locations which are further used for the bus route optimization model in the next section.

5.4.1.2 Optimization Model for Bus Routes

The marshal point locations obtained from the previous section identify the nodes of the network that will become the skeletal emergency transit network. The bus routes are identified from the existing set of bus routes. This study uses existing bus routes because of the network familiarity of transit users, drivers, and control room operators being an important factor for an efficient evacuation. The existing set of bus routes are obtained from 2012 Halifax Geodatabase. Note that according to the current traffic rules in Halifax, cars are restricted to transit priority corridors when the bus lane is in effect. Marshal points contained within each route in the existing set are spatially identified. Marshal points contained in more than one transit routes are separately identified. The scheduled travel time is obtained from 'Halifax Transit'. If a set of transit routes is R, then the existing set of routes can be expressed as follows:

$$R = \{r_1, r_2, r_3, r_4 .... r_n\} \tag{2}$$

where, r_i are the route IDs.

If the set of marshal points identified is M, and the set of travel time for routes is T_R, then these two sets can be presented as below:

$$M = \{M_1, M_2, M_3, M_4 .... M_n\} \tag{3}$$

$$T_R = \{T_1, T_2, T_3, T_4 .... T_n\} \tag{4}$$

Next, a parameter a_{nr} is introduced to denote whether a marshal point lies on a route. Below is a description of the parameter:

$$a_{nr} = \begin{Bmatrix} 1, & \text{if } M_n \text{ is on route, } r_i \\ 0, & \text{Otherwise} \end{Bmatrix} \tag{5}$$

The following problem is then solved to determine the optimum bus routes, which yields minimum travel time and assigns at least one route to each marshal point.

Objectives:

$$Minimize \sum_{r \in R} p_r * T_r \tag{6}$$

Subjected to:

vii. $\sum_{r \in R} a_{nr} * p_r \geq 1, \quad \forall n$

viii. $p_r = \{0,1\}$

p_r is a binary variable that takes value 1 if route r_i is selected, and 0 otherwise. There are two constraints in the optimization problem: constraint (vii) states that each marshal point must be assigned to at least one route, and constraint (viii) describes the binary variable p_r.

In total, 135 marshal points out of 488 bus stops are identified through optimization modelling of marshal point locations. The number of marshal points chosen per route for one direction ranges from 9 to 22. The optimization process determines 12 bus routes to serve all 135 marshal points.

5.4.1.3 Evaluation of Solution Approach

The computation time is significantly smaller in the case of the implemented solution approach compared to traditional algorithm. To illustrate the improvements, the MILP problem is solved using "Branch and Bound" algorithm and the performance result is compared to that of the proposed solution approach. **Figure 5-1** demonstrates the improvement in relative MIP gap over time achieved by both solution approaches. The MIP gap refers to the fractional gap between the integer objective and the objective of the best remaining node.

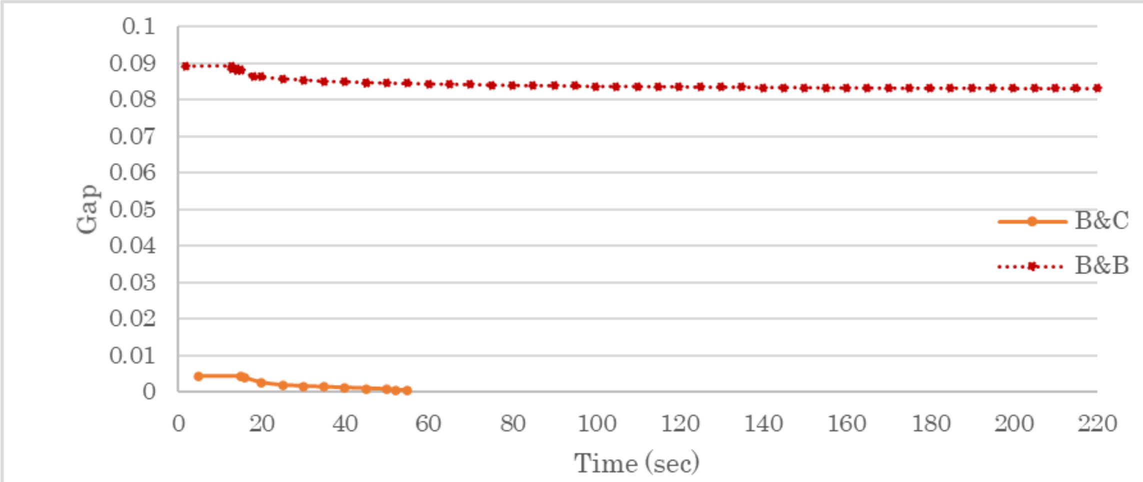


Figure 5-1 Efficiency of "Branch and Bound (B&B)" and "Branch and Cut B&C)" algorithm

The results in **Figure 5-1** suggest that the B&C algorithm outperforms B&B. It expeditiously achieves the desired gap and provides the optimal solution. The B&B method decreases the relative gap gradually with time and cannot provide the optimal solution within the same time incurred by B&C method. Moreover, the relative gap is always higher in B&B method, while the optimum solution is obtained by B&C method with negligible MIP gap.

5.4.2 Multimodal Traffic Evacuation Microsimulation Model

5.4.2.1 Network Coding

This study develops a multimodal evacuation microsimulation model by including necessary transit network components into an auto-based evacuation microsimulation model, which was developed by Alam et al. (2018) for Halifax, Canada and presented in the previous chapter. The revised microscopic traffic simulation model contains altogether 1784 links and connectors that results in a road network of a total length of 480 km. The model still contains 41 major signalized and 12 stop sign-controlled intersections with 2813 resolved turning conflicts in the network. The updated evacuation microsimulation model contains 56 peninsula TAZs in alignment with the zoning system of the Halifax regional transport network model. The evacuation demand is updated, and the estimated new evacuation demand is 65,000 by auto and 8,400 by bus. In total, 12 transit routes and 135 marshal points obtained from optimization models are coded within the updated traffic evacuation microsimulation model. The number of waiting passengers (x_{zs}) at marshal points is estimated through the optimization model and used to develop a bus-boarding-volume profile at each marshal point. The bus schedule is coded for each bus route. In total, 174 sixty-seated buses from Halifax Transit are used to evacuate the transit-dependent population; this was an average figure for Halifax Transit, while, standing room or articulated buses with higher capacity could be considered. As mentioned earlier, the two designated shelters used for evacuation in this study are C. P. Allen High School and Nova Scotia Community College (NSCC). The first shelter is located 15 km away from the Peninsula, located at the end of the Bedford Highway and can be reached through Highway 102 and the second one is 9 km away from the peninsula taking the two bridges as travel routes.

5.4.2.2 Calibration and Validation of the Multimodal Evacuation Microsimulation Model

This chapter uses the calibrated values of driving behaviour parameters obtained through LHS techniques and link surcharge values obtained through route choice calibration in Chapter 4. A traffic volume-based validation similar to Chapter 4 is conducted to examine the deviation between the observed and simulated traffic volumes at key locations. A goodness-fit of the multimodal evacuation microsimulation model is found as 0.81 and 0.82 in terms of R^2 for two morning peak hours 0700-0800 and 0800-0900, respectively.

5.5 Results and Discussions

5.5.1 Multimodal Evacuation Performance Evaluation

This study evaluates the performance of a multimodal evacuation from all traffic analysis zones to designated shelters through the Halifax transport network. **Figure 5-2** shows the hourly percent cumulative arrival of auto users and the transit-dependent population when considering a multimodal evacuation in the Halifax Peninsula.

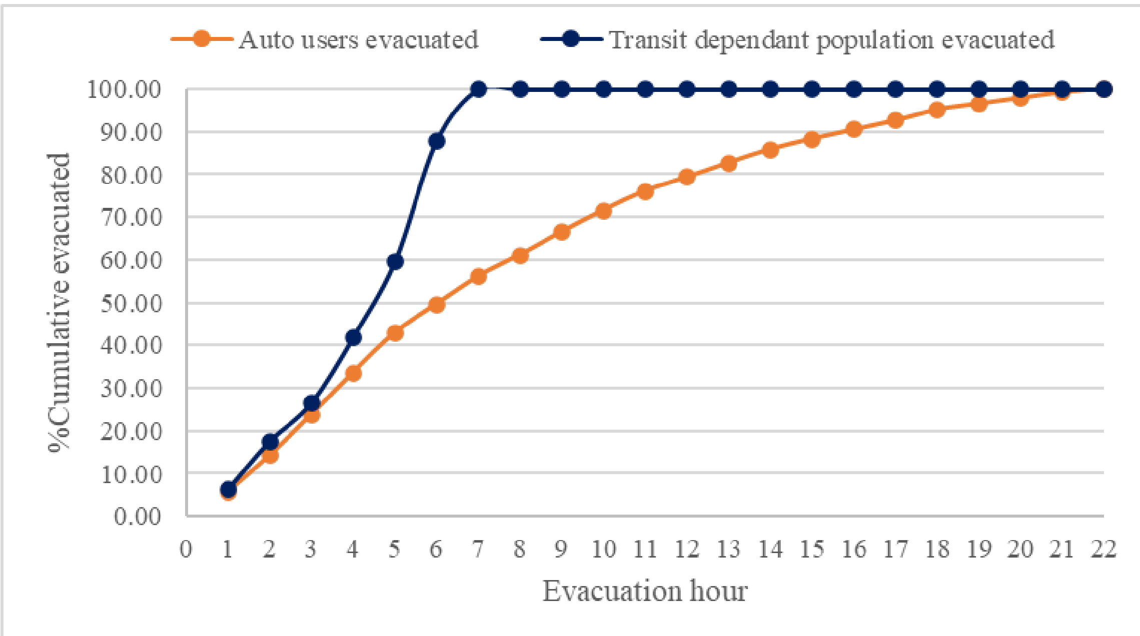


Figure 5-2 Percent cumulative evacuation of auto and transit users with progression of evacuation time

The results from simulation reveal that it requires twenty-two hours to evacuate auto users from the peninsula, while evacuation of the transit-dependent population is completed within seven hours. A longer time with auto evacuation is mainly due to 'at once' evacuation at peak time through the narrow roads of a historical city like Halifax with limited access points. The transit evacuation results demonstrate an excess capacity of the transit system to provide transportation assistance for additional evacuees who might switch from auto and other modes. The simulation enables buses to use full capacity depending on the availability of the demand at marshal points. Hence, evacuation of the transit-dependent population is rapid compared to evacuation of auto users when only transit-dependent populations are assumed to be evacuated by buses. At the ninth hour of evacuation, 70% of auto users arrive at shelters, which demonstrates a complete evacuation of 90% of TAZs in the peninsula. The remaining 10% of the zones predominantly in the downtown area that have a higher evacuation demand. The introduction of a larger demand of this nature within a short period creates localized congestion in the downtown network, particularly across arterial and key loading links, resulting in a slower evacuation process for these zones. Therefore, it can be concluded that there are certain zones that show significant delays in evacuation, which warrants a consideration for special evacuation plans, including staged evacuation, among others.

This study also presents average travel time distribution at different cutoff times of the evacuation from all zones to shelter 1 and shelter 2, respectively (**Figure 5-3a** and **Figure 5-3b**). Results in **Figure 5-3** show that at the initial time of evacuation, average travel time increases significantly for most of the zones. Travelling to shelter 1 requires relatively a higher travel time, which varies between 2-3 hours. More specifically, residents from 70% of the zones experience an average travel time of 1 - 2 hours to safely reach shelter 1 at the most congested periods of evacuation. This study also examines mode-specific travel time for multimodal evacuation. The simulation results suggest that average travel time for auto is 31.44 minute and 37.76 minutes for bus.

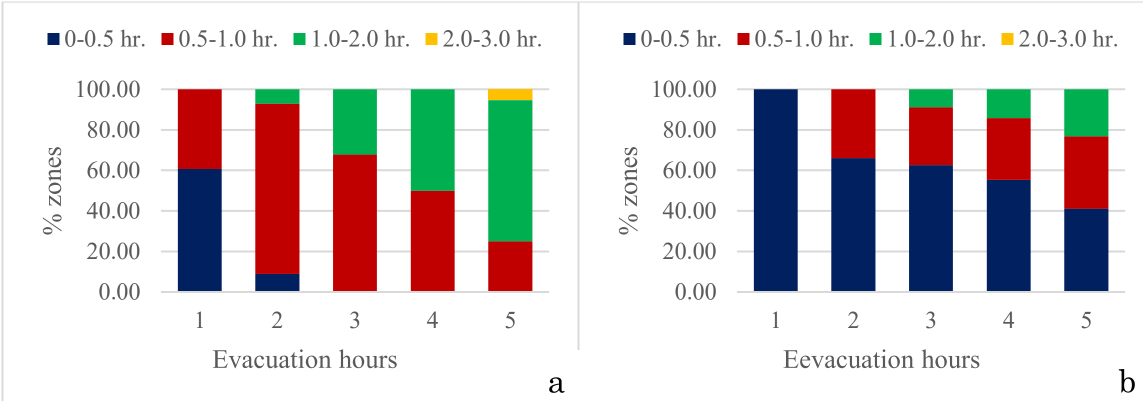


Figure 5-3 Average travel time distribution at different cut-off times of the evacuation from zones to (a) shelter 1 and (b) shelter 2.

Figure 5-4 presents a frequency distribution of travel time for both auto and bus. The results show that approximately 69% of drivers experience a travel time equal to or less than average travel time (31.44 minutes), while the fraction is around 78% for buses, corresponding to an average travel time of 37.76 minutes. 50% of auto require a travel time of 25 minutes or less, while for 50% of buses, it requires 30 minutes or less. Arguably, additional time is added to average bus travel time due to stops at marshal points.

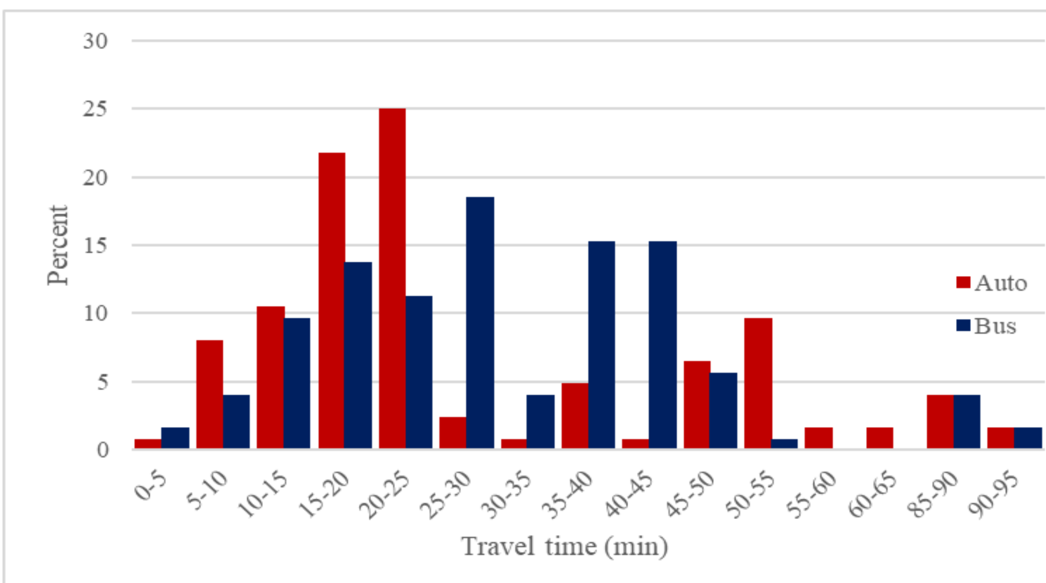


Figure 5-4 Mode-specific travel time distribution for multimodal evacuation of the Halifax peninsula

Travel time is slightly longer for transit users; however, with the benefit of higher bus capacity, the complete evacuation of transit users is faster than the evacuation of auto users as shown in **Figure 5-2**.

5.5.2 Transit Evacuation Performance Evaluation

5.5.2.1 Transit Demand Served

Further analysis of optimization and simulation results focuses on evacuation demand served at different marshal points along transit lines. **Figure 5-5** illustrates all transit lines and marshal points obtained from the optimization models and presents the spatial distribution of transit demand served during the evacuation. The results show that most of the marshal points are concentrated in the Downtown core and South-End of the Peninsula. The derived transit lines overlap in different parts of the Peninsula, particularly in the downtown core, which results in 43 marshal points being served by multiple transit lines. This study measures the performance of marshal points served by 1, 1+, 2+ and 3+ transit lines. **Table 5-2** shows that average demand served by 2+ marshal point is 2.7%, while this value is 1.04% and 1.8% for 1 and 1+ marshal point, respectively.

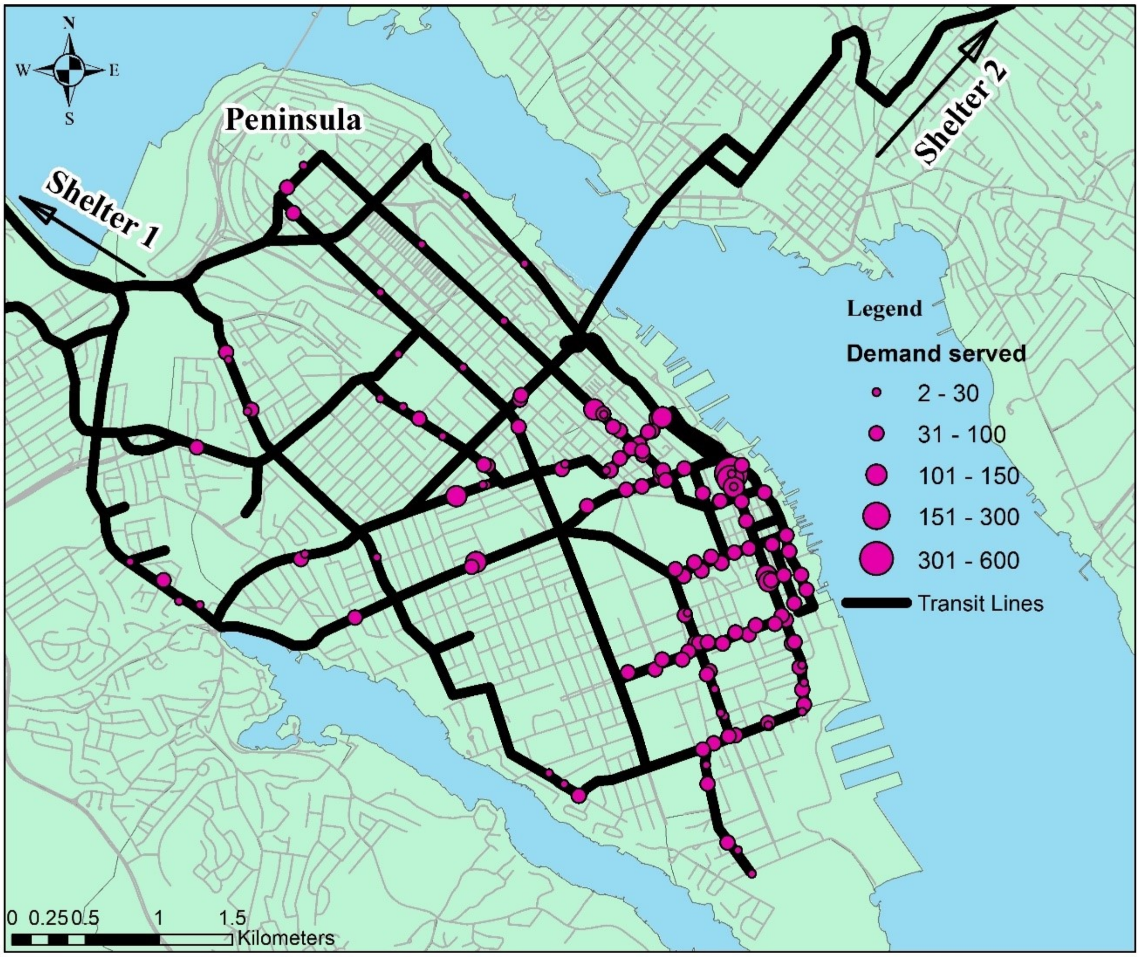


Figure 5-5 Spatial distribution of transit demand served at marshal points along transit lines

Table 5-2 Transit Demand Served by Different Categories of Marshal Points

Marshal points served by transit lines	% of total transit demand served	% average demand served by each marshal point
1	58	1.04
1+	19	1.8
2+	15	2.7
3+	8	0.7

5.5.2.2 Traffic Congestion along Transit Lines and Critical Links

Spatial and temporal variation of traffic congestion along transit lines are examined in terms of average speed. Average speed is estimated at link level for different times of evacuation. **Figure 5-6** presents average speed distribution for all transit lines in the network. The results from simulations suggest that average speed is relatively lower near exits, across key links of the downtown core of the Peninsula. Transit lines passing over arterial streets experience significant traffic congestion, as these streets primarily lead traffic to shelters through the highways, the roundabout, and the bridges. This study also presents temporal variation of traffic congestion during evacuation. **Figure 5-7** shows that average speed is below 30 km/h for most transit lines until the fifth hour of evacuation. Following this, average speed improves, and traffic operates at around 35-40 km/hr. after the congested periods. This result will help determine the offsetting time of transit operations during an emergency.

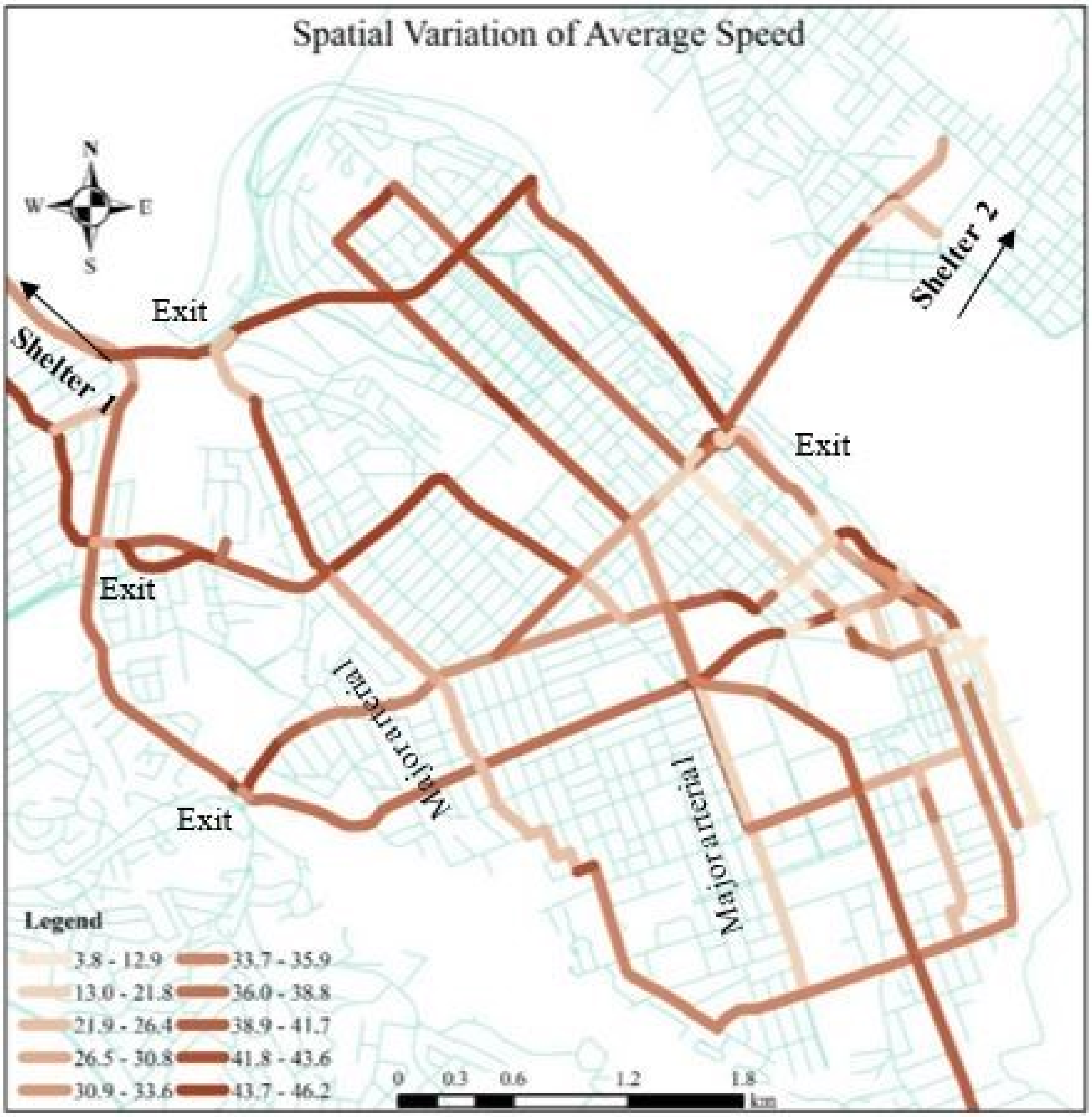


Figure 5-6 Spatial variation of traffic congestion propagation measured in terms of average speed along transit lines and critical links

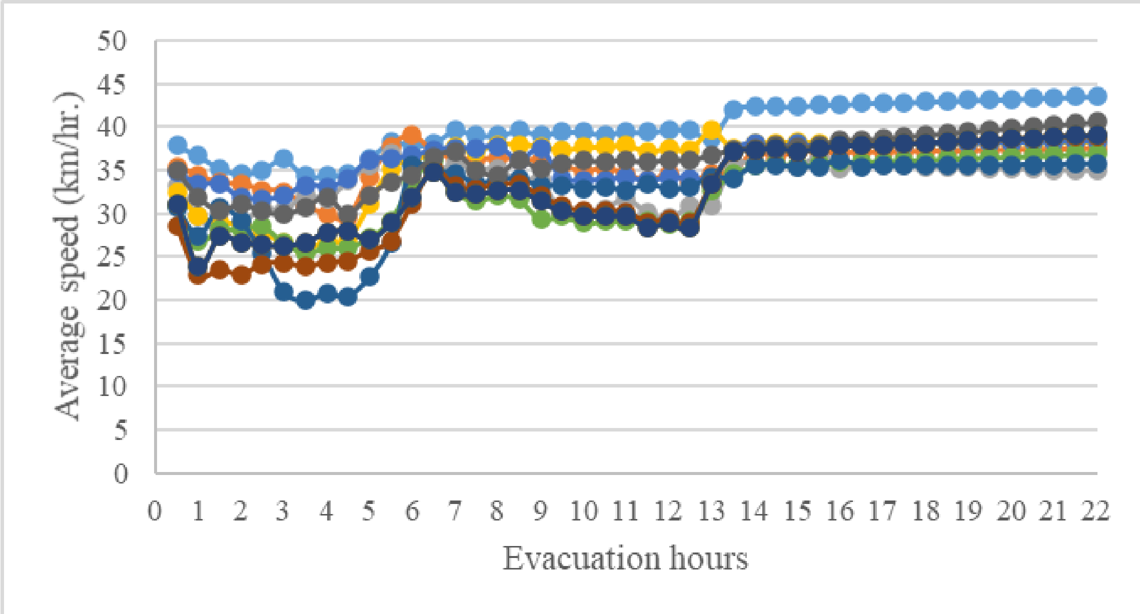


Figure 5-7 Temporal variation of traffic congestion propagation measured in terms of average speed along transit lines

5.5.2.3 Pick-up and drop-off of Transit Passengers

The study also analyzes the pick-up and arrival patterns of transit passengers. The simulation results, as shown in **Figure 5-8,** suggest that pick-up rate decreases and arrival rate at shelters increases with the progression of evacuation time.

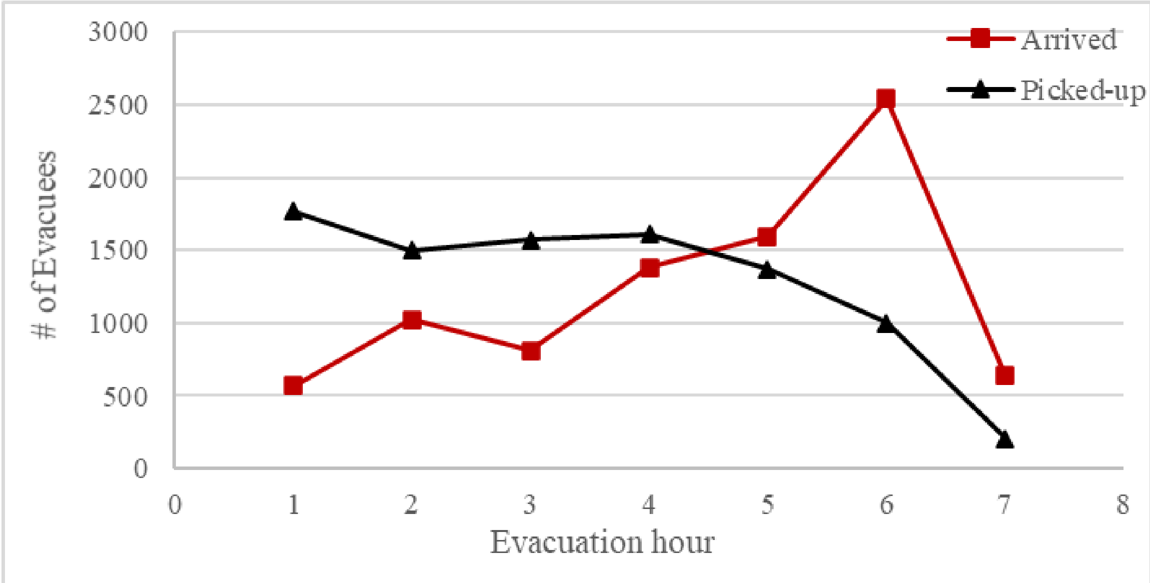


Figure 5-8 Pick-up and arrival pattern of transit dependent population with progression of evacuation time

Initially, the deviation between the number of individuals picked-up and dropped-off is higher. After 4.5 hours, demand for pick-up becomes lower in the network than the number of transit users arrived at shelters. **Figure 5-8** shows that the arrival of transit users at shelters peaks in the sixth hour of evacuation. At this hour, buses are best utilized and 30% of buses operate in the network to serve marshal points. It urges a pre-bus evacuation planning to intersect two times demonstrating the peak bus demand and bus utilization.

5.6 Conclusions

This chapter presented a multimodal evacuation microsimulation model that incorporates strategic planning decisions, including marshal point location and transit route choice decisions. The model tests and evaluates network conditions with multimodal evacuation plans. One of the key contributions of this study is that it develops a novel solution approach "Branch and Cut" to solve the proposed MILP-based marshal point location and transit route choice problem while addressing transit demand under emergency conditions.

The proposed framework was empirically tested for a case study in Halifax, Canada. This study addressed the transportation needs of the transit-dependent population in assessing a mandatory multimodal evacuation of the Halifax Peninsula. The optimization solution approach used in this study achieved optimum results faster with a negligible relative MIP gap compared to that of other traditional methods. The optimization process identified 135 marshal points and 12 transit routes to serve around 8,400 transit-dependent individuals. This study simulated an evacuation operation where buses continued to pick up evacuees until they reached capacity or no demand was left at marshal points, depending on which occurred first. The optimization results informed the multimodal evacuation scenario-building process for the simulation model. The simulation of multimodal evacuation anticipated a duration of 22 hours to completely evacuate auto users, which is alarming for coastal city Halifax. However, the transit-dependent population was completely evacuated within 7 hours of the evacuation. The results also revealed that traffic congestion was the highest at the core of the peninsula. Additionally, average speed was found lower near exits. The congestion results will help to identify critical time segments of evacuation for transit operations.

This study contributes to the literature by developing a multimodal evacuation microsimulation model that evaluates network conditions for a multimodal evacuation. The results provide insight into public transportation planning, including marshal point locations, and transit route choices for emergency evacuation, and managing multimodal evacuation traffic operations. It is to be noted that this study assumes that evacuees have full awareness regarding marshal point locations, and they will choose one based on their network familiarity and that they use frequently during their daily travel. However, how to communicate evacuees and disseminate information among them is not explored in this research. It warrants the development of communication and dissemination plan to update evacuees with necessary information. Nevertheless, the results help emergency professionals and engineers to identify the excess capacity of the transit system that can accommodate for additional evacuees who might switch from other modes.

However, the study found that evacuating all citizens at once takes a longer time since spillback gridlocks the narrow roads of the town. The condition can be exacerbated with other complexities and disruption risks associated with evacuation. The next chapter incorporates uncertainties and further evacuation disruption risks such as vehicle collision within the developed traffic evacuation microsimulation model. Such evacuation model combining vehicle collision prediction and traffic simulation model will be useful for an estimation of the upper limit of evacuation times.

Chapter 6

Modelling Traffic Disruptions[3]

6.1 Introduction

This chapter presents a traffic evacuation microsimulation model that accounts for traffic disruption risks in assessing a mass evacuation scenario. The evacuation of an urbanized population has become critical due to the increased concentration of population, business centers, economic infrastructures, and the resulting traffic congestion in the transport network. The world is currently facing unanticipated challenges due to frequent natural disaster events such as a hurricane and is under threat to manmade disasters such as a terrorist attack. The transportation system, a vital element of urban infrastructure, is vulnerable to natural and manmade catastrophes that may lead to a low level to a cascading failure of the system. The transport network plays a vital role in connecting people and delivering goods between distant places. Any disruption to a road network due to natural or man-made disasters could have a significant consequence including long-stranded traffic queues and unbound economic losses (Wisetjindawat et al. 2019; Tsuchiya and Okada 2007). The issue is even more critical during an emergency evacuation when a

[3] This chapter is largely derived from the following peer-reviewed journal papers:

- Alam, M. J., and Habib, M. A. (2020). Modelling Traffic Disruptions during Mass Evacuation. *Procedia Computer Science*, 170, 506-513
- Alam, M.J., and Habib, M.A (2021). Mass evacuation microsimulation modelling considering traffic disruptions. *Natural Hazards*. https://doi.org/10.1007/s11069-021-04684-y

transport network is only the means to move the affected people from the endangered area. Mostafizi et al. (2017) showed that tsunami related disruptions to several key links in the network increases the mean mortality rate by 5%. Alam et. al. (2017a) estimated a travel time delay cost of $22,000 in the morning peak period due to a sudden 1-hour construction-related bridge closure in Halifax, Canada. Existing evacuation modelling research focuses more on the natural disaster related disruption risks. However, given the extent of the impacts of sudden network disruptions inherent to the traffic operations (Alam et al. 2017a; Alam et al., 2017b; Zhu et al. 2012), predicting collision rates is of paramount importance to assess the risks holistically when considering a mass evacuation. Accommodating for vehicle collision-related network disruptions within the evacuation modelling framework urges to develop an evidence-based probabilistic approach to identify the most likely collision locations, alternatively, the 'hotspot'. Simultaneously, it is of utmost importance to investigate the effects of collision-related congestion spillback on the surrounding network and the total network clearance time. The capability of traffic microsimulation models to track each individual and represent heavily congested transport network has made them a good candidate for evacuation modelling in a disrupted network. Additionally, an advanced traffic microsimulation model with dynamic routing capacity is ideal to portray the disrupted and diverted evacuation traffic flows. Few studies (Wisetjindawat et al. 2019; Tsuchiya and Okada 2007; Alam et al. 2018) addressed natural disasters such as flooding or tsunami related network damages within the traffic evacuation simulation model. However, accounting for disruption risks inherent to the transport operations is almost absent, which requests further attention to comprehensively assess evacuation parameters during an emergency condition. This study aims to combine collision prediction and traffic microsimulation modelling for evacuation testing within the disrupted network resulting from the incidents inherent to the traffic operations.

Therefore, the objective of this study is to develop a probabilistic model to identify collision hotspots, and a mechanism for accounting collision related disruptions within traffic evacuation microsimulation model. In this study, a probabilistic model follows a combined Bayes theory and Monte Carlo simulation approach to identify hotspots at different times of an evacuation day. Unlike other studies, instead of placing pseudo collision disruptions by updating the link capacity, this study uses the proposed probabilistic model to internally implement the hotspots on the links in the traffic microsimulation model. The traffic evacuation microsimulation model is updated with network disruption information to test and evaluate evacuation scenarios in a disrupted network.

6.2 Literature Review

Traffic microsimulation model has gained popularity in evacuation research as it enables accommodating for the impacts of natural disasters, the network's vulnerability to uncertain incidents and policy decisions when simulating evacuation plans. In addition, an advanced dynamic traffic microsimulation model is capable of reliably predicting driver's re-routing in response to the sudden collision disruptions during an evacuation. Despite the advantage of traffic simulation modelling, simulations involving uncertain network disruptions are limited for mass evacuation. Network vulnerability has adequately been researched over the past few years (Günneç and Salman 2011; Sohn 2006; Dalziell and Nicholson 2001; Jenelius and Mattsson 2012; Tang and Huang 2018). These studies estimated the vulnerability of the road network to natural disasters, including earthquakes and floods. Network vulnerability due to natural catastrophes has further been evaluated in combination with an evacuation event. For example, it has been found that natural disaster related network damage delays the complete evacuation and/or causes incomplete evacuation (Alam et al. 2018). Bae et al. (2014) considered network disruptions due to a hypothetical bomb blast in the network, where affected links are considered inactive from the start of the evacuation. This study evacuated people on a shortest-path basis; however, dynamic traffic congestion propagation due to network disruptions was not addressed. Mostafizi et al. (2017) determined the mortality rate against a tsunami moving inland. Several studies (Ferguson 2011; Watts et al. 2012; Huang et al. 2009) considered the traffic impacts of construction related network disruptions during daily commuting traffic conditions. Other studies (Jenelius 2010; Sohn 2006) focused on the network redundancy by observing the performance of a link when other links were disrupted in the network. Although, several research, for example, Li et al. (2015) investigated the traffic patterns and highway disruptions during hurricane Irene and Sandy, they did not analyze the effects of disruptions on evacuation traffic flows. However, the study asserted that there is limited difference in collision locations and occurrences pattern under both the evacuation and business as usual conditions. While network vulnerability and daily traffic flow disruptions are adequately addressed, an evacuation performance is rarely evaluated in the presence of uncertain collision-related network disruptions. Given the necessity of an efficient road transport system for an evacuation, it is critical to predict the locations where disruptions are most likely to occur in the network. This is also of paramount importance to identify the potential areas where the collision-related impacts would be the most severe during a mass evacuation.

Li and Ozbay (2015) utilized a conditional probability function to accommodate disruptions in the network by a cell-based modelling method, which considered that the likelihood of a collision occurrence is a function of traffic flows. The hypothetical disruption scenarios considered in the earlier studies either assumed pre-defined link closures or made capacity adjustments to the network links to replicate disruptions. They utilized a traffic flow data-driven conditional probability to identify collision locations. In this regard, locations that have lower traffic flows may be overlooked but be at risk of a collision due to other factors including roadway conditions. Moreover, during evacuation, the entire network has the potential to be grid-locked, which may overestimate the overall network disruptions when using the conditional probability function over only the volume-capacity ratio. In addition to traffic flow-related factors, there are other crucial factors including road surface conditions, alignment, and driver's distraction that contribute to the likelihood of a collision occurrence. This study identifies key factors in collision occurrence for determining the candidate collision locations that further informs the hotspot identification process. A probabilistic modelling approach is adopted to estimate the candidate location's probability to anticipate a vehicle collision. In this regard, the Bayes theory appears to be the most advantageous tool which enables determining the posterior probability of an event given the prior probability of the occurrence of that event.

This study adopts a combined Bayes theory and Monte Carlo simulation approach to determine the hotspots using the identified candidate collision locations. The Monte Carlo simulation technique is employed to predict hotspots involving collisions at different times of day. This study utilizes a traffic microsimulation model to explicitly incorporate disruptions informed by the proposed probabilistic model. The sudden nature of collision occurrence is replicated by developing disruptions in the middle of the evacuation simulation. Evacuation efficiency and network performance are evaluated in terms of traffic flow density, queue propagation, percent completion of evacuation, and travel time changes.

6.3 Data Used

This study uses the Nova Scotia Collision Record Database (NSCRD) for developing models. The data was obtained from Service Nova Scotia and Municipal Relations (SNSMR). All police reported collisions that occurred between 2007 and 2011 in Halifax, Canada are extracted from NSCRD. The database contains details regarding the time, location, and characteristics of the individuals involved in a collision. Additional information includes vehicle type, weather, lighting, driver conditions, and crash configuration. The NSCRD data includes road related information including the attributes road grade, road configuration, road surface, road divider, and road alignment pertaining to reported collisions. The attributes are further described by several sub-attributes, for example, the attribute 'road grade' is characterized by slope, level, and other road grade conditions. Moreover, age and gender information associated with each collision record in the dataset are also available. Additionally, the database records collisions due to driver's distraction. Distraction types in the dataset include distraction by communication device, distraction by vehicle display, distraction due to inattention, and others. The data processing obtained 67,985 collision records that are occurred in Halifax. This study utilizes the collision data observed on a normal day traffic condition. It does not incorporate extraordinary human responses in the analysis. The rationale to use all collisions is mainly to predict hotspots where traffic safety issue exists and the collisions during panic conditions are likely to occur projected by five years of historical collision data. However, if the data observed on an evacuation day would be available, it can be useful to accommodate human factors into collision probability analysis.

6.4 Methodology

This chapter develops a probabilistic model to identify hotspots where a collision is most likely to occur in the network. A combined Bayes theory and Monte Carlo simulation approach is adopted to determine the spatial and temporal distribution of the hotspots involving collisions. The identified hotspots are incorporated within a traffic microsimulation model to account for disruptions during a mass evacuation. The overall framework for the proposed modelling approach is presented in **Figure 6-1**.

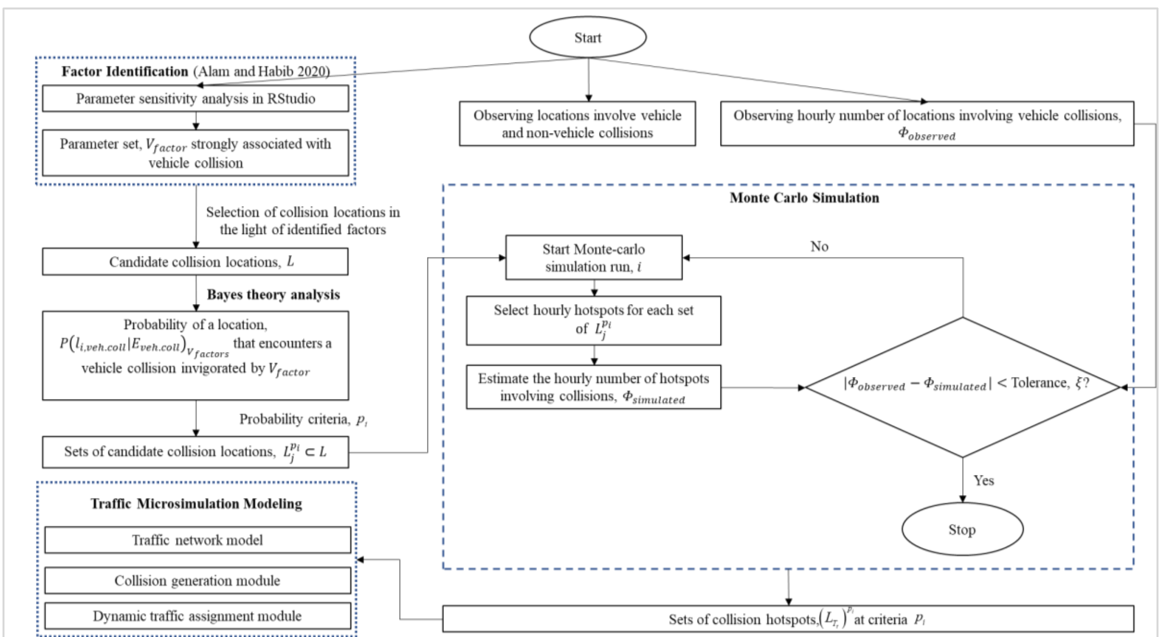


Figure 6-1 A comprehensive framework of collision hotspot identification for traffic evacuation microsimulation modelling

6.4.1 Collision Hotspots Identification

This study follows three stages to predict collision hotspots in the network: (1) identification of candidate collision locations utilizing contributing factors in vehicle collision occurrence, (2) determination of the likelihood of a candidate location to anticipate a vehicle collision using a Bayes theory-based probabilistic model, and (3) identification of the hotspots for different times of a day using a Monte Carlo simulation approach.

6.4.1.1 Candidate Collision Locations

This study identifies candidate collision locations based on the factors affecting the likelihood of collision occurrence. The study conducts a sensitivity analysis of fifty-six variables that involve individual characteristics including age and gender, roadway conditions, such as road surface and alignment, and drivers' distraction types associated with each collision reported in NSCRD. The data covering 2007 to 2010 collisions are used for identifying influential factors. In the sensitivity analysis, each parameter that has a confidence interval excluding the null hypothesis (zero effects in magnitude) is identified (**Figure 6-2**).

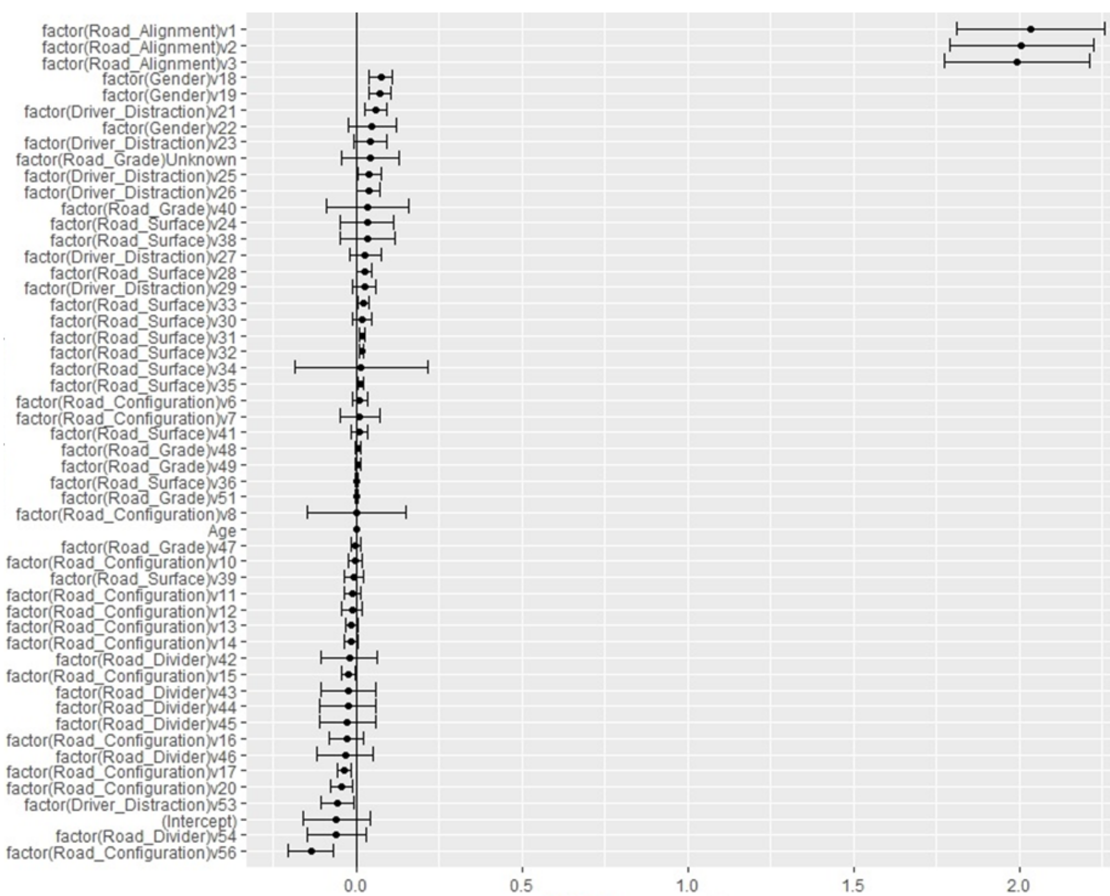


Figure 6-2 Estimation of fifty-six variables affecting collision occurrence

In **Figure 6-2**, horizontal bar represents the confidence interval bounded by a minimum and a maximum value. Bars that lie on the right side of the 'zero effect line', and do not contain 'zero' demonstrate the significant association of the corresponding variables with the occurrence of vehicle collisions. A total of thirteen parameters under four categories are identified that demonstrate significant contributions to the vehicle collision occurrence as shown in **Table 6-1**. The sensitivity analysis conducted in this study helps understand the factor types and their contributions to potentially triggering a vehicle collision.

Table 6-1 Factors Affecting Collision Occurrence Identified through the Sensitivity Analysis

Road surface	Road alignment	Distraction	Gender
Loose or excess sand, gravel, or dirt (v_{28}) Conf. Interval: [0.003, 0.046] Effects: 0.024; P: 0.0267	Others (v_1) Conf. Interval: [1.810, 2.259] Effects: 2.034; P: 0.0000	Not distracted (v_{21}) Conf. Interval: [0.026, 0.093] Effects: 0.059; P: 0.0005	Female (v_{18}) Conf. Interval: [0.039, 0.108] Effects: 0.074; P: 0.0000
Fresh and loose snow (v_{31}) Conf. Interval: [0.01, 0.025] Effects: 0.018; P: 0.0000	Curved (v_2) Conf. Interval: [1.789, 2.224] Effects: 2.006; P: 0.0000	Distracted, inattentive (v_{25}) Conf. Interval: [0.006, 0.073] Effects: 0.04; P: 0.0204	Male (v_{19}) Conf. Interval: [0.038, 0.106] Effects: 0.072; P: 0.0000
Icy (v_{32}) Conf. Interval: [0.009, 0.024] Effects: 0.016; P: 0.0000	Straight (v_3) Conf. Interval: [1.776, 2.211] Effects: 1.993; P: 0.0000	Others (v_{26}) Conf. Interval: [0.003, 0.070] Effects: 0.037; P: 0.0336	-
Packed snow (v_{33}) Conf. Interval: [0.007, 0.038] Effects: 0.022; P: 0.0050	-	-	-
Slush, wet snow (v_{35}) Conf. Interval: [0.006, 0.021] Effects: 0.014; P: 0.0006	-	-	-

To identify the candidate collision locations, this study utilizes key factors listed in **Table 6-1**. The locations where the factors contribute to collision occurrence are flagged as candidate collision locations. The collection of the factors can be represented by $V_{factors}$, and the set of candidate collision locations can be represented by L, where:

$$V_{factors} = \{v_1, v_2, v_3, ...v_t\} \tag{1}$$

$$L = \{l_1, l_2, l_3, ...l_n\} \tag{2}$$

A candidate collision location may involve a vehicle and/or a non-vehicle collision. After the identification process of candidate locations, a Bayes theory approach is used to evaluate candidate locations in relation to the vehicle collision occurrence.

6.4.1.2 Candidate Location Probability for a Vehicle Collision: A Bayes Theory Approach

This study adopts a Bayes theory-based approach (Bayes 1763) to estimate the probability of a candidate location to anticipate a vehicle collision when the prior knowledge of the conditions related to the event is given. Let's assume, $E_{veh.coll}$ represents an event of a vehicle collision at a location l_i where $l_i \in L$. $E_{other.coll}$ refers to an event of a non-vehicle collision. $V_{factors}$ is a set of key factors that have a large association with the occurrence of vehicle collisions $E_{veh.coll}$. Now, the following formula can be utilized to estimate the probability of a location $P\left(l_{i,veh.coll} \mid E_{veh.coll}\right)_{V_{factors}}$ to anticipate a vehicle collision.

$$\begin{aligned} P\left(l_{i,veh.coll} \mid E_{veh.coll}\right)_{V_{factors}} &= \frac{P(E_{veh.coll} \mid l_{i,veh.coll})_{V_{factors}} * P(l_{i,veh.coll})}{P(E_{veh.coll})_{V_{factors}}} \\ &= \frac{P(E_{veh.coll} \mid l_{i,veh.coll})_{V_{factors}} * P(l_{i,veh.coll})_{V_{factors}}}{P(E_{veh.coll} \mid l_{1,veh.coll})_{V_{factors}} * P(l_{1,veh.coll}) + P(E_{veh.coll} \mid l_{2,veh.coll})_{V_{factors}} * P(l_{2,veh.coll}) + ...(E_{veh.coll} \mid l_{i,veh.coll})_{V_{factors}} * P(l_{i,veh.coll})} \end{aligned} \tag{3}$$

where,

$P\left(l_{i,veh.coll} \mid E_{veh.coll}\right)_{V_{factors}}$ represents the probability of a candidate location to anticipate a vehicle collision.

$P(E_{veh.coll} \mid l_{i,veh.coll})_{V_{factors}}$ represents the probability of a vehicle collision occurrence given a location l_i.

$P(l_{i,veh.coll})$ represents the probability of observing a candidate location l_i for vehicle collision occurrence.

Following the process, the computation estimates the probability for each candidate location $l_i \in L$ that anticipate a vehicle collision. The probabilities are then utilized to categorize the candidate locations into several groups by introducing different levels of probability criteria. The multiple sets of candidate locations allow to test and evaluate scenarios representing different levels of disruptions and complexity during a mass evacuation. Let p_i represent a set of probability criterion and $L_j^{p_i}$ the set of all sub - sets of candidate locations corresponding to criteria p_i as expressed in equation 4.

$$L_j^{p_i} = \left\{L_1^{p_1}, L_2^{p_2}, L_3^{p_3} \text{..........} L_k^{p_k}\right\} \tag{4}$$

Where, $L_1^{p_1}, L_2^{p_2}, L_3^{p_3} \text{..........} L_k^{p_k} \subset L$, $L_1^{p_1} \cap L_2^{p_2} \cap L_3^{p_3} \cap \text{..........} \cap L_k^{p_k} \neq \phi$, $p_i = \left\{p_1, p_2, p_3, \ldots p_k\right\}$, and $j = \left\{1, 2, 3 \text{.........} k\right\}$. The equation 4 indicates that any location, l_i may have a membership to more than one subset of $L_j^{p_i}$.

Although all the candidate collision locations have potential to anticipate a vehicle collision, it is unlikely that all of them would anticipate a collision at the same time on a specific day. Therefore, this study implements a Monte Carlo simulation process to identify the hotspots involving collisions from different sub-sets of candidate locations for different times of an evacuation day.

6.4.1.3 Temporal Distribution of Hotspots Involving Collisions: A Monte Carlo Simulation Approach

In this stage, hotspots involving collisions are drawn from each element of $L_j^{p_i}$ for different hours of an evacuation period using a Monte Carlo simulation technique. Thus, each element of $L_j^{p_i}$ generates a sub-set of hotspots and all the sets of hotspots are collectively represented by $\left(L_{T_t}\right)^{p_i}$. Each sub-set of $\left(L_{T_t}\right)^{p_i}$ represents a collection of hotspots for different evacuation hours T_t corresponding to probability criteria p_i as formulated in equation 5.

$$\left(L_{T_t}\right)^{p_i} = \begin{cases} \left\{(l_1,l_2......l_i)_{T_1},(l_1,l_2......l_i)_{T_2},..........(l_1,l_2......l_i)_{T_t}\right\}^{p_1},\left\{(l_1,l_2......l_i)_{T_1},(l_1,l_2......l_i)_{T_2},..........(l_1,l_2......l_i)_{T_t}\right\}^{p_2} \\ .....\left\{(l_1,l_2......l_i)_{T_1},(l_1,l_2......l_i)_{T_2},..........(l_1,l_2......l_i)_{T_t}\right\}^{p_k} \end{cases} \quad (5)$$

$$\left(L_{T_t}\right)^{p_i} = \left\{\left\{(h_i)_{T_t}\right\}^{p_1},\left\{(h_i)_{T_t}\right\}^{p_2}........\left\{(h_i)_{T_t}\right\}^{p_k}\right\}$$

where, $i=\{1,2,3........n\}$, $\left\{(h_i)_{T_t}\right\}^{p_1},\left\{(h_i)_{T_t}\right\}^{p_2}..........\left\{(h_i)_{T_t}\right\}^{p_k} \subset L_1^{p_1},L_2^{p_2},L_3^{p_3}..........L_k^{p_k} \subset L$, $\left\{(h_i)_{T_1}\right\}^{p_1} \cap \left\{(h_i)_{T_2}\right\}^{p_2} \cap .... \cap \left\{(h_i)_{T_t}\right\}^{p_k} \neq \phi$, and $t=\{1,2,3,........t\}$. i represents location IDs and same location can be selected at different hours within the same subset of $\left(L_{T_t}\right)^{p_i}$ and across different subsets if the location satisfies for multiple probability criteria.

To validate the distribution of collision occurrence at hotspots, $\phi_{simulated}$ over the evacuation hours T_t under each probability criteria p_i, an hourly distribution, $\phi_{observed}$ over the same period is obtained from the NSCRD 2011. The Monte

Carlo simulation is continued until the simulated distribution, closely matches with the observed distribution obtained from the provided dataset. The Monte Carlo simulation is implemented using Visual Basic of Applications (VBA) and includes the following steps:

- Step 1: Start Monte Carlo simulation run, r to select hotspots randomly from $L_j^{p_i}$ for evacuation period T_t, where $r = \{1, 2, 3........n\}$.
- Step 2: Compare the simulated distribution, $\phi_{simulated}$ with the observed distribution, $\phi_{observed}$.
- Step 3: If the deviation between two distributions is less than the desired threshold ζ, stop simulation.
- Step 4: If not, return to Step 1 to run simulation $r+1$.

At the end of Monte Carlo simulation, one or more hotspots for vehicle collision occurrence at different hours are determined, which are to be coded into the traffic evacuation microsimulation model. The mechanism to accommodate for disruptions within the traffic microsimulation model is described in section 6.6.

6.5 Evacuation Scenarios considering Traffic Disruptions

6.5.1 Candidate Collision Locations and Probabilities

This study recognizes thirteen factors (V_{factor}) that significantly contribute to the collision occurrence at candidate locations. In total, 128 candidate collision locations ($l_i \in L$) are identified in this study (**Figure 6-3**). Following a Bayes theory-based probability computation, the likelihood of candidate location, $P\left(l_{i,veh.coll} \mid E_{veh.coll}\right)_{V_{factors}}$ to anticipate a vehicle collision is estimated. **Figure 6-3** presents all the candidate locations that may anticipate a vehicle collision with a likelihood of 0.21% - 7%. **Figure 6-4** shows the kernel density of collision occurrence obtained from the Bayes probability analysis for the study area. The results reveal that the downtown core, commercial area and exit locations are highly likely to anticipate a vehicle collision.

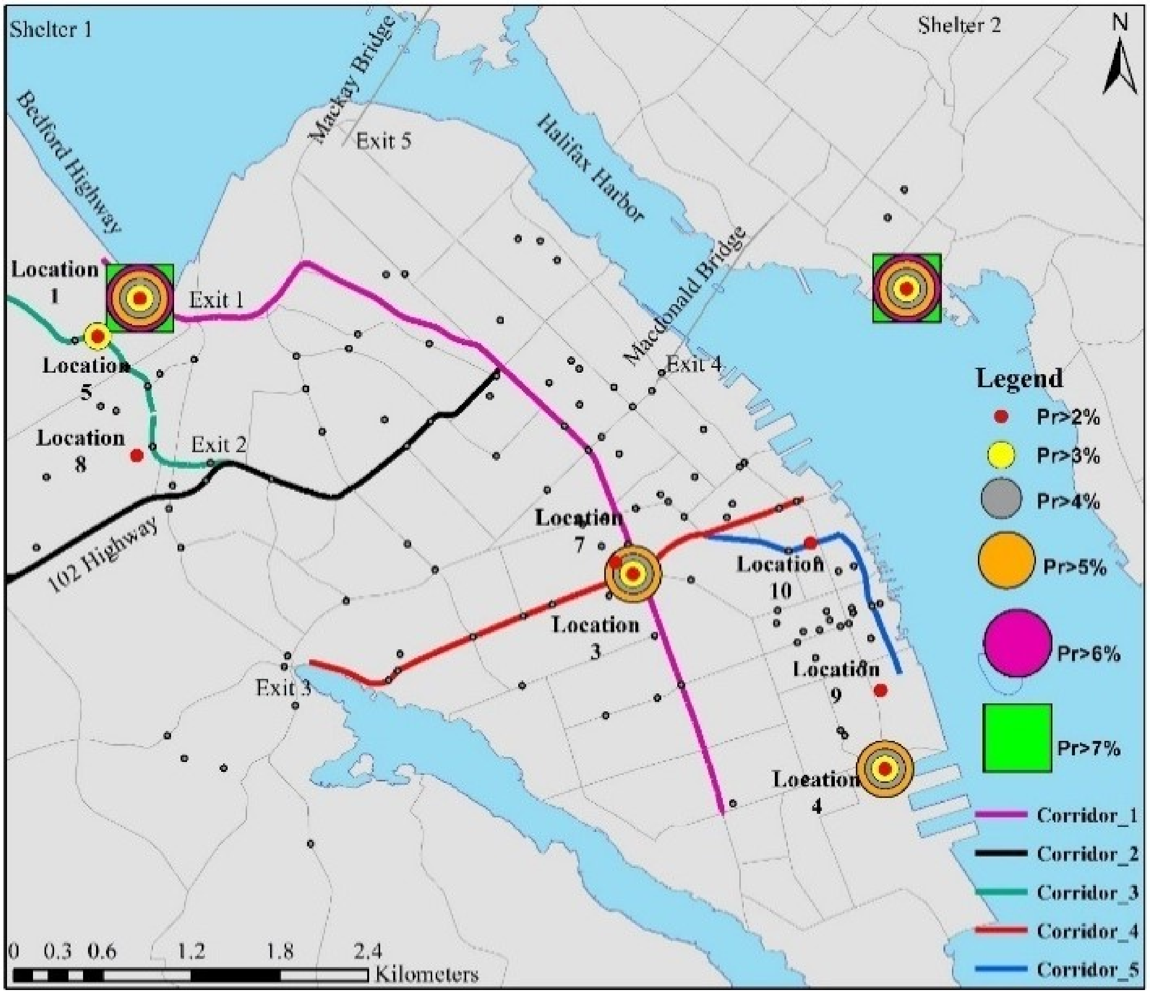


Figure 6-3 Visualization of all collision locations, hotspots for each probability criteria and major corridors for network performance analysis

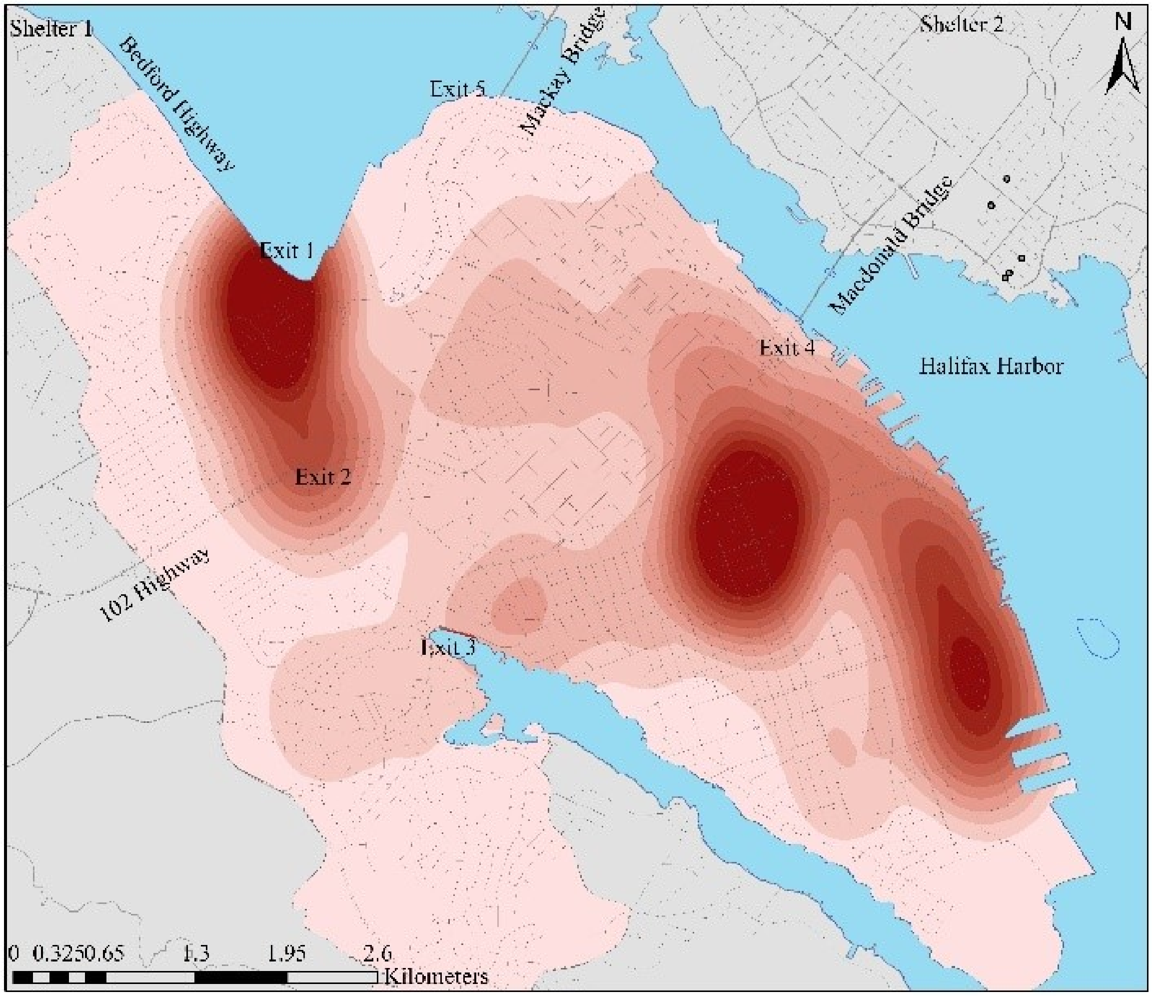


Figure 6-4 Kernel density of collision occurrence

Figure 6-3 illustrates several major corridors that are used for traffic impact analysis in this study. Both red and multicolored locations represent the hotspots obtained by Monte Carlo simulation described in the next section. Multicolor indicates that these locations satisfy in different probability criteria p_i.

6.5.2 Hotspots in Evacuation Period

Four probability criteria (p_i) are introduced, taking probability values of equal to or greater than 2%, 3%, 4%, and 5% for candidate locations to anticipate a collision, which results in four sub-sets of candidate collision locations $L_j^{p_i}$. Each subset is subjected to a Monte Carlo simulation for determining hotspots, $(L_{T_t})^{p_i}$ at different times of an evacuation. Consequently, four sets of hotspots are obtained in relation to the four probability criteria shown in **Table 6-2**. Hotspots that are drawn for generating vehicle collisions, but that do not affect traffic movement within the evacuation area are excluded. For example, **Table 6-2** shows that scenario 1 considers only a location (i.e., location 7) while two locations were drawn through the Monte Carlo simulation for the period 1700-1800.

Table 6-2 Number of Hotspots and Hotspot IDs at Different Hours of Evacuation Period for Each Probability Criteria (p_i)

Evacuation hours	Scenario 1: $p_1 \geq 2\%$		Scenario 2: $p_2 \geq 3\%$		Scenario 3: $p_3 \geq 4\%$		Scenario 4: $p_4 \geq 5\%$	
	Hotspot# from Monte Carlo Simulation	Hotspot considered $(L_{T_t})^{p_1}$	Hotspot# from Monte Carlo Simulation	Hotspot considered $(L_{T_t})^{p_2}$	Hotspot# from Monte Carlo Simulation	Hotspot considered $(L_{T_t})^{p_3}$	Hotspot# from Monte Carlo Simulation	Hotspot considered $(L_{T_t})^{p_4}$
T_1 : 1000-1100	1	No	1	No	1	No	1	No
T_2 : 1100-1200	1	No	1	No	1	No	1	Loc 7
T_3 : 1200-1300	1	Loc 1	1	No	1	Loc 3	1	Loc 5
T_4 : 1300-1400	1	Loc 10	1	No	1	No	1	No
T_5 : 1400-1500	1	Loc 3	1	No	1	Loc 10	1	Loc 10
T_6 : 1500-1600	2	No	1	No	1	No	1	No
T_7 : 1600-1700	2	No	1	Loc 7	1	No	1	Loc 3
T_8 : 1700-1800	2	Loc 7	1	No	1	Loc 1	1	Loc 1
T_9 :1800-1900	2	Loc 5	2	Loc 5	1	Loc 7	1	No
T_{10} : 1900-2000	1	No	1	Loc 10	1	No	1	No
T_{11} : 2000-2100	1	No	1	Loc 3	1	Loc 5	1	No

The simulated distribution of collision occurrence at hotspots is compared to the observed distribution for the given evacuation period. **Figure 6-5** presents the deviation between the observed and simulated percent collisions at hotspots where the values deviate by 3% or less at each hour.

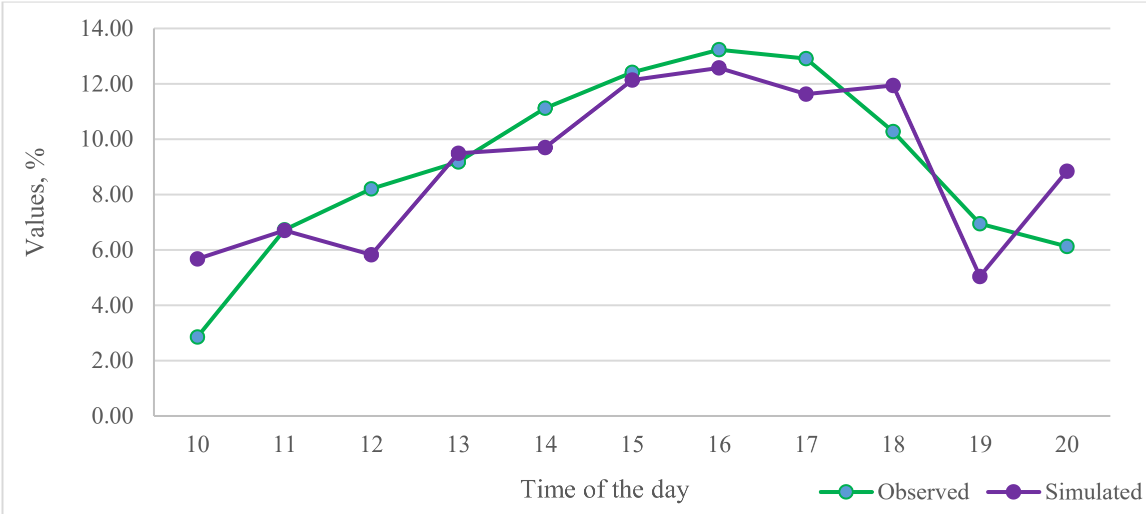


Figure 6-5 Observed and simulated distribution of collision occurrence at hotspots obtained from NSCRD and Monte Carlo simulation, respectively

Starting with a 10% deviation between the observed and simulated distribution at the first run of the Monte Carlo simulation, this study achieved a deviation of 3% or less after 62,407 simulation runs. In **Table 6-2**, four scenarios regarding four probability criteria are presented in which collisions occur at different hours of an evacuation period. Apart from these, this study introduces an additional scenario that considers collisions taking place concurrently at the selected hotspots. Therefore, the evacuation scenarios to be evaluated in this study broadly include (1) Base case scenario: no disruptions, (2) Scenario 1 – 4: staggered disruptions, and (3) Scenario 5: concurrent disruptions. This study simulates the above evacuation scenarios considering two disruption conditions: removal and non-removal of traffic disruptions. The time for collision occurrence in **Table 6-2** ranges from evacuation hour 10:00 to 21:00. A starting time of 10:00 is due to the assumption that the population doubles in the morning within the study area presenting a critical evacuation scenario. A period of 10:00 to 21:00 is selected for a traffic disruption analysis based on the data revealing that collision occurrence is significant at this period. The collection of candidate collision locations, $L_j^{p_i}$, sets of hotspots

$\left(L_{T_t}\right)^{p_i}$ for all probability criteria (p_i) are shown previously in **Figure 6-3**. Now, according to the proposed framework in **Figure 6-1**, the hotspots involving collisions are to be coded into the traffic microsimulation model for evaluation.

6.6 Traffic Microsimulation Modelling considering Traffic Disruptions

To generate collision-related disruptions to the evacuation traffic flow at the hotspots identified, the traffic evacuation microsimulation model developed in the previous chapters is utilized (Alam et al., 2018; Alam et al., 2019). Collision-related disruptions are coded within the simulation model using the signal concept, where a red light represents a disruption at the specified time in the signal controller. **Figure 6-6** presents all five scenarios with temporal distribution of collision occurrence at hotspot considering a non-removal of traffic disruption condition in the network.

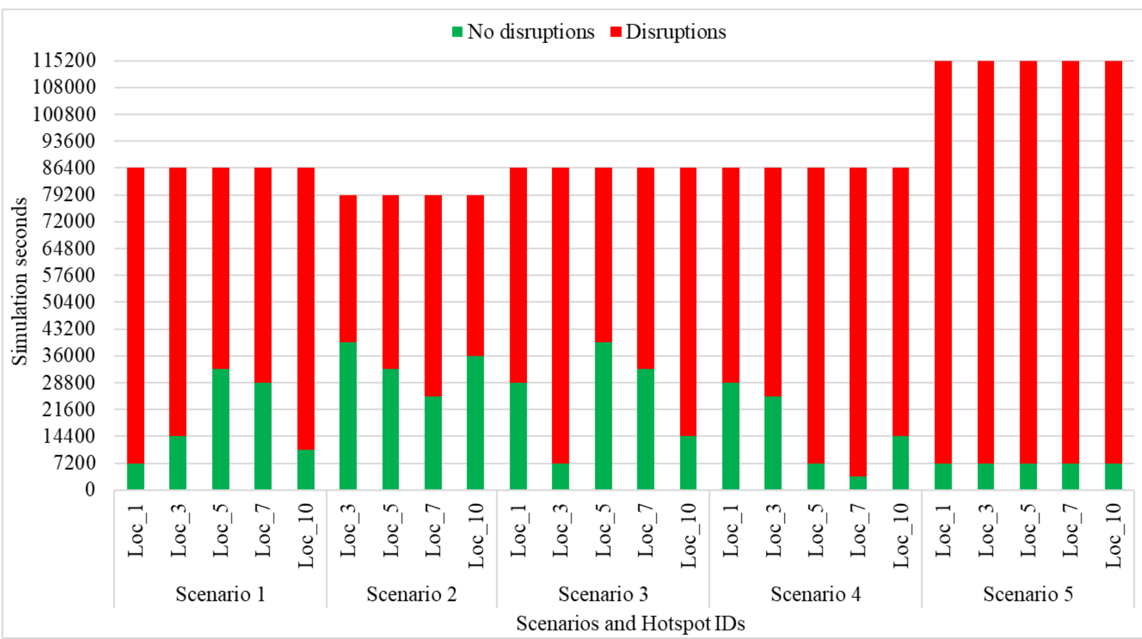


Figure 6-6 Coding of disruptions at hotspots within the traffic microsimulation model

It shows the length of red and green time in signal groups to represent a vehicle collision at a certain hotspot in different scenarios. As mentioned earlier, signal controller consists of signal phases and signal groups. A 'red-green' phase is used in this study to activate collisions at specified hotspots and times. In total, five new signal controllers are placed at five hotspots identified through the probabilistic model.

6.7 Results and Discussions

This study explores the impacts of collisions on a mass evacuation process considering a removal of traffic disruption condition utilizing a traffic evacuation microsimulation model. However, the study also presents the worst-case evacuation scenarios considering a non-removal of traffic disruption condition, because during panic situation, there might be circumstances at some hotspots making it difficult to remove the disruptions given the limited time and accessibility issues.

As mentioned earlier, four scenarios (scenario 1 – 4) demonstrating staggered collision occurrence and scenario 5 representing concurrent collision occurrence at hotspots are considered for analyzing a mass evacuation under both removal and non-removal of traffic disruption conditions. A base case scenario involving no collisions in the network is also assessed. It has been observed that the staggered collision occurrence increases evacuation time by 4.5% with respect to a base case scenario if the traffic disruption is removed in 2 hours or less. **Table 6-3** shows that it takes same evacuation time in both staggered and concurrent collision occurrence scenarios if traffic disruption is removed in 2 hours or less. However, in the case of a removal time above 2 hours, it takes 24 – 33 hours to evacuate the peninsula depending on the removal time of traffic disruptions from the network in concurrent collision occurrence scenario.

Table 6-3 Overall Evacuation Time for Two Collision Scenarios considering the Removal of Traffic Disruptions

Scenario Types	Removal of Traffic Disruption	
	In ≤ 2 hours	In > 2 hours
Staggered Disruptions	23	24-25
Concurrent Disruptions	23	24-33

This study also examines the evacuation time under concurrent collision occurrence scenario in relation to different times required to remove traffic disruptions from the network. **Figure 6-7** illustrates that the evacuation time is 23 hours if traffic disruption is removed in 2 hours or less and climbs up to 31 hours if the disruption is removed in >2 – 24 hours.

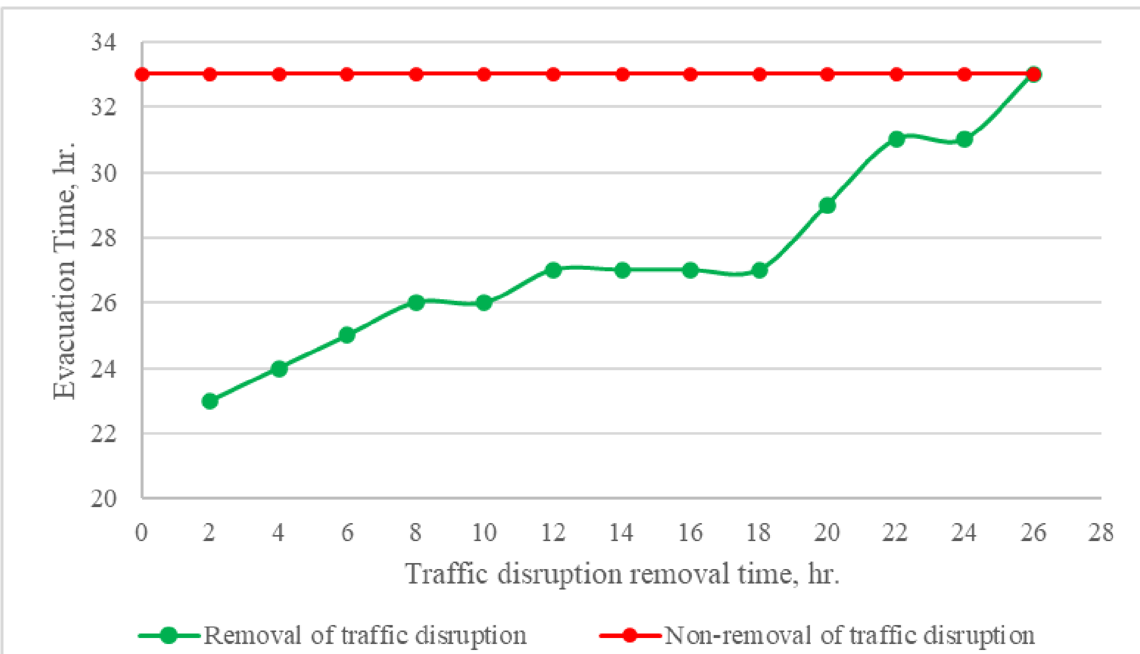


Figure 6-7 Evacuation time in relation to the traffic disruption removal time in the network under a concurrent collision occurrence scenario

In non-removal of traffic disruption condition, it takes 33 hours to evacuate the peninsula. The following sections focus on further analysis of the results from traffic microsimulation model for both removal and non-removal of traffic disruption cases. The scenario evaluations are carried out in terms of evacuation completion, queue length, travel time and clearance time.

6.7.1 Removal of Traffic Disruption

6.7.1.1 Evacuation Completion and Travel Time Analysis

This study analyzes the impacts of staggered collision occurrence on evacuation traffic flows considering the removal of traffic disruptions as shown in **Figure 6-8.**

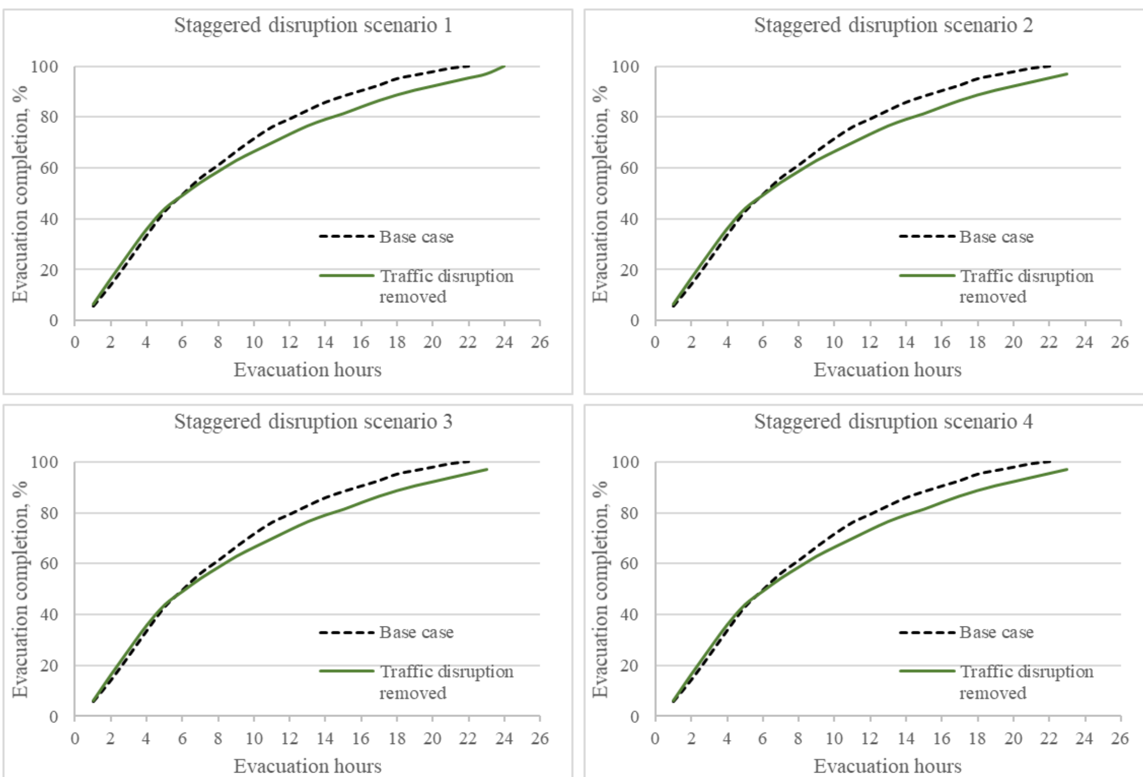


Figure 6-8 Visualization of percent cumulative evacuation completion for base case, and staggered collision occurrence scenarios under the removal of traffic disruption condition

Figure 6-8 shows percent cumulative traffic flows for base case, and staggered collision occurrence scenarios considering the removal of traffic disruptions from the network. The diagrams do not suggest a significant deviation between the lines representing base case and staggered collision occurrence scenarios. Although, changes in traffic flow indicators at regional level are not significant, local level impacts are evident when comparing travel time results from both removal and non-removal of traffic disruption cases. **Figure 6-9** illustrates a box plot of individual travel time in the network and indicates that individual travel time is relatively lower in the case of removal of traffic disruptions case.

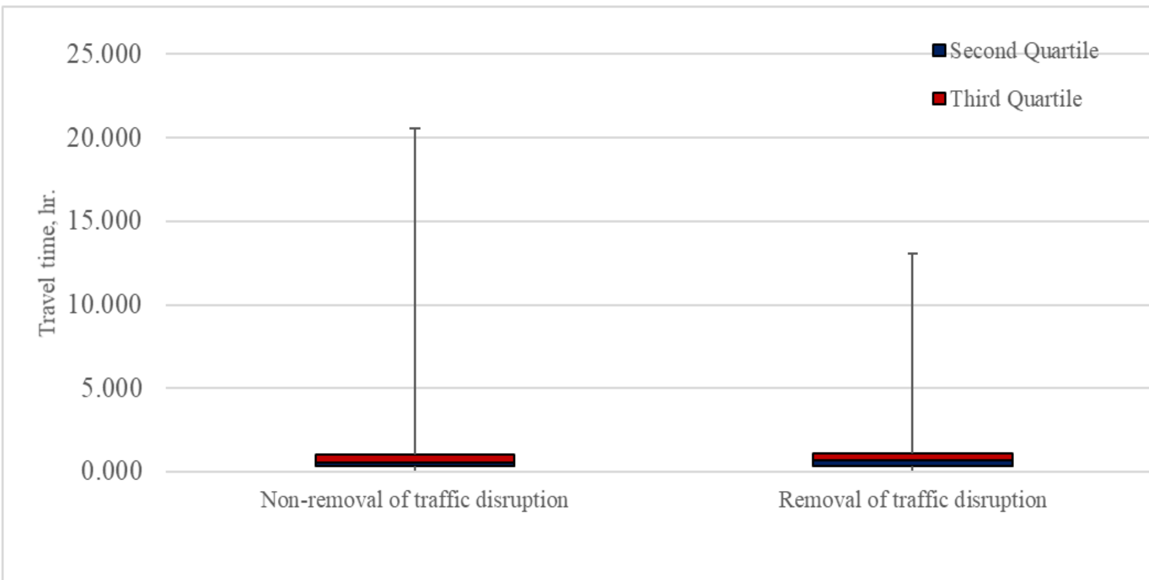


Figure 6-9 A box plot analysis of individual travel time during an evacuation considering staggered collision occurrence

In the case of concurrent collision occurrence scenario, evacuation time is way higher with respect to the base case scenario. **Figure 6-10** shows that with the increase in the removal time of traffic disruption from the network, traffic throughputs drop, and evacuation time increases.

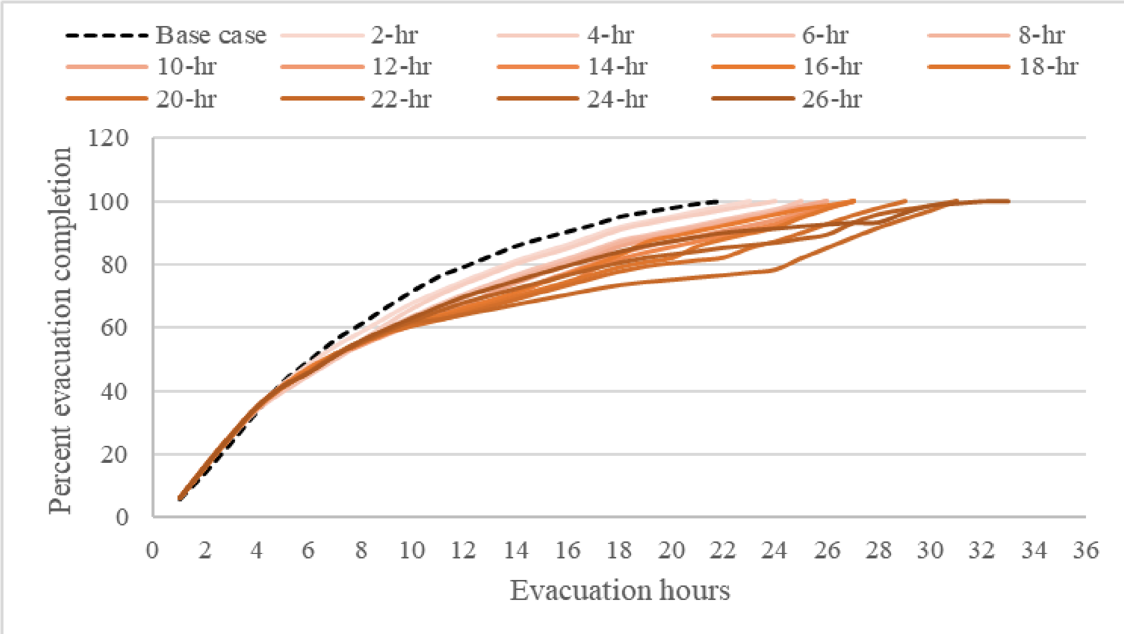


Figure 6-10 Percent cumulative completion of evacuation in concurrent collision occurrence scenario in relation to the removal time of traffic disruptions in the network

Furthermore, the study also explores the impacts of concurrent collision occurrence at individual level as shown in **Figure 6-11**.

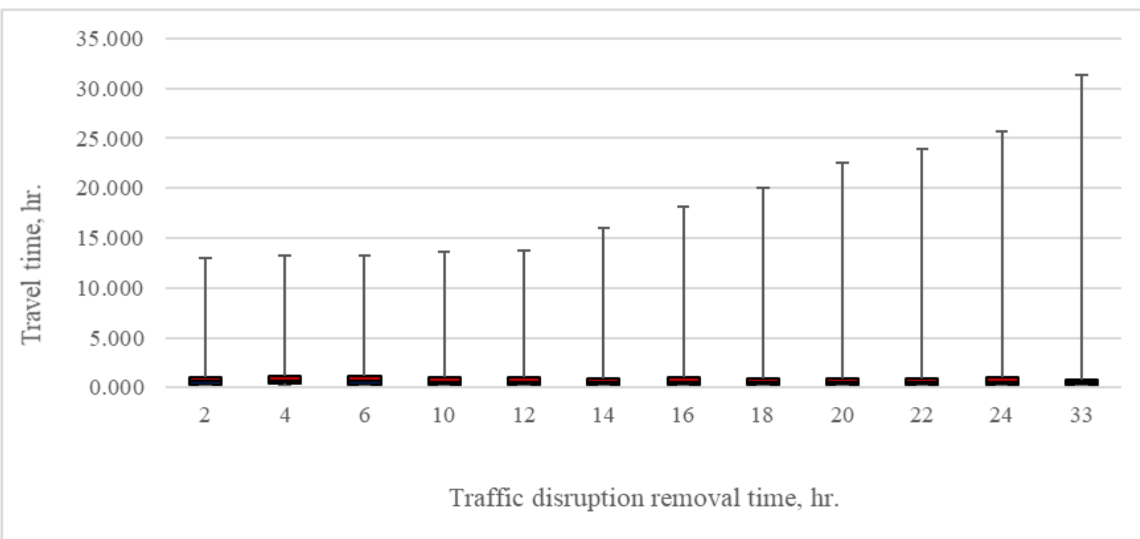


Figure 6-11 Individual travel time analysis in concurrent collision occurrence scenario considering the removal of traffic disruptions in the network during an evacuation

Figure 6-11 presents the individual travel time when the disruptions are removed at different hours of evacuation period. Results show that 75% individuals anticipate approximately a similar travel time regardless of the time required to remove traffic disruption from the network. However, 25% individuals represented by the top whisker anticipate a minimum travel time of 13 hours in the network. In this study, scenario 5 is found to be the worst-case scenario and is considered for further analysis.

6.7.1.2 Clearance Time Analysis

This study also assesses zonal clearance time considering the concurrent collision occurrence at hotspots. Clearance times are observed in relation to the time required for removing traffic disruption from the network. The study divides the Halifax Peninsula into four planning districts for analysis purpose. **Table 6-4** shows the effects of traffic disruption of varying durations on the zonal clearance time for four planning districts such Downtown (DT), West-End (WE), North-End (NE), and South-End (SE). Each row represents a traffic analysis zone within a certain planning district.

Table 6-4 Zonal Clearance Time Visualization in relation to the Traffic Disruption Removal Time considering Concurrent Collision Occurrence

Planning Districts	Traffic disruption removal time, hr.										
	2hr	4hr	6hr	10hr	12hr	14hr	16hr	18hr	20hr	22hr	24hr
DT	12.08	10.58	12.25	12.83	15.08	18.25	18.67	20.83	23.00	24.58	26.67
	9.92	12.42	13.33	16.50	18.42	16.83	19.92	20.58	22.67	29.17	26.67
	7.17	9.50	11.25	12.58	14.42	16.42	18.67	20.33	22.42	24.42	26.58
	12.08	10.92	14.92	14.92	17.67	22.83	18.67	25.58	26.67	27.50	27.67
	24.08	24.00	25.92	25.92	24.33	31.92	24.25	30.83	31.42	31.92	31.92
	6.92	8.92	8.58	12.58	14.50	16.42	18.50	20.67	23.25	24.50	26.67
	25.92	25.92	25.92	25.92	30.83	27.08	31.92	26.08	25.92	31.92	27.08
NE	7.17	8.50	25.92	12.50	14.50	16.42	18.42	31.92	22.50	24.50	26.67
	11.42	14.75	8.67	13.50	15.42	16.33	9.42	10.75	13.42	24.33	26.42
	6.50	7.92	8.50	6.08	5.92	5.92	5.92	6.67	6.42	24.25	6.67
	25.17	25.58	25.92	25.92	20.83	31.92	23.17	31.92	31.92	31.92	31.92
	9.42	7.00	8.25	6.08	6.17	5.83	6.08	6.50	6.42	6.17	7.17
	7.00	8.17	8.25	6.08	6.33	5.75	5.75	6.67	6.67	5.92	6.92
	6.50	7.92	7.17	5.83	5.83	5.75	5.67	20.50	6.83	6.75	7.08
	14.42	20.00	13.00	12.83	14.58	16.67	18.58	20.58	22.50	24.58	26.67
	6.92	7.75	15.58	6.33	14.33	11.42	6.08	6.67	6.50	24.33	26.33
	6.92	8.00	8.33	6.33	6.42	5.75	5.75	6.50	6.83	24.42	26.25
	5.58	7.08	7.17	6.08	5.75	9.42	7.42	6.08	11.42	11.42	6.92
	6.42	8.17	8.42	5.75	6.17	5.92	5.83	6.67	6.25	24.25	26.42
	6.42	8.75	7.33	6.17	6.08	6.00	6.08	6.25	6.67	24.25	7.17
	5.25	11.75	8.50	15.50	6.42	6.00	6.08	6.50	6.25	6.33	6.00
	7.08	7.83	8.25	6.33	10.42	5.92	11.42	6.67	6.67	24.33	26.33
	5.83	7.83	8.25	6.08	6.08	6.00	6.08	6.08	6.58	6.00	6.00
	14.42	7.67	8.42	6.17	6.42	6.00	6.00	6.75	6.75	24.33	26.33
	7.00	7.50	8.42	5.83	6.50	6.00	6.08	6.75	6.58	6.75	6.58
	7.08	9.08	7.58	12.58	14.33	16.67	18.50	20.42	6.67	24.50	26.50
	7.25	8.67	8.50	6.33	14.33	16.42	6.08	20.58	6.83	24.42	26.33
SE	10.33	9.50	11.75	12.92	15.00	17.92	18.67	20.92	23.08	24.58	26.67
	7.83	9.50	8.83	12.75	14.67	16.58	18.67	20.50	22.50	24.50	26.67
	7.08	8.92	8.50	12.42	14.42	16.42	6.33	20.42	22.42	24.42	26.50
	9.58	9.42	12.00	13.58	17.08	16.58	18.67	21.75	25.75	24.50	26.50
	9.25	10.75	11.92	12.92	16.42	16.58	18.67	22.58	25.33	24.50	26.50
	7.33	9.25	10.42	12.83	14.75	17.58	18.67	21.00	22.92	25.25	26.67
	10.83	13.75	10.17	14.50	14.92	16.75	18.67	20.83	22.75	24.58	26.58
	15.42	7.33	8.50	7.50	5.83	5.92	6.00	13.75	12.42	24.25	7.00
	7.00	8.83	8.75	12.42	14.33	10.17	18.58	20.58	22.58	24.42	26.17
	8.17	9.25	9.33	12.83	15.00	16.50	18.42	20.83	23.00	24.50	26.33
	7.75	9.17	9.25	12.83	14.92	16.33	7.67	20.83	22.75	6.83	7.58
	9.58	9.42	12.08	13.75	17.58	16.67	18.67	22.08	25.75	24.50	26.33
	6.92	9.17	8.83	12.50	14.58	16.92	18.58	20.50	22.83	24.58	26.50
	9.75	9.08	11.00	12.92	14.83	17.75	18.67	20.92	22.92	24.67	26.67
WE	6.33	16.75	8.25	10.50	8.42	13.42	16.42	5.92	6.83	24.25	7.08
	13.42	7.00	8.42	6.00	5.67	5.92	15.42	15.75	16.42	24.25	7.08
	6.08	7.33	12.58	16.50	6.00	16.25	6.08	6.42	15.42	24.25	26.33
	8.42	7.17	14.58	13.92	14.33	16.92	5.75	20.33	7.42	24.33	26.33
	4.25	7.75	4.25	6.50	7.42	4.33	13.42	4.25	14.42	16.42	4.25
	6.25	6.67	9.58	13.33	6.08	16.83	6.25	6.75	7.08	6.17	6.08
	5.83	6.92	16.58	6.17	5.75	10.42	5.83	8.75	6.42	13.42	15.42
	6.00	15.75	10.58	6.17	14.42	5.83	10.42	5.92	6.67	8.42	6.92
	5.92	12.75	8.58	5.92	5.67	5.83	5.92	11.75	6.25	6.00	6.58
	6.25	7.00	8.67	5.67	5.67	5.83	5.75	14.75	6.42	6.00	9.42
	5.42	6.33	7.25	5.83	16.42	5.42	12.42	5.83	6.25	6.33	6.75
	5.42	6.08	8.67	5.75	5.75	5.83	5.67	5.83	6.58	6.08	5.67

Table 6-4 shows that NE zones are marginally affected if the collision is removed in 2-20 hours. WE zones are directly connected to three exits making them partially immune to traffic disruptions during evacuation. DT being the city centre and SE, being located at the corner of DT, zones in these two

districts are significantly affected by the collisions even the disruption is rapidly removed in 2 hours.

6.7.2 Non-Removal of Traffic Disruption

6.7.2.1 Evacuation Completion Analysis

This study estimates arrival rates of evacuees at different times of an evacuation period for all scenarios, i.e., no disruption (base case scenario), staggered disruptions (scenario 1 – 4) and concurrent disruptions (scenario 5). **Figure 6-12** presents the cumulative completion of evacuation in all cases considering no removal of traffic disruptions from the network.

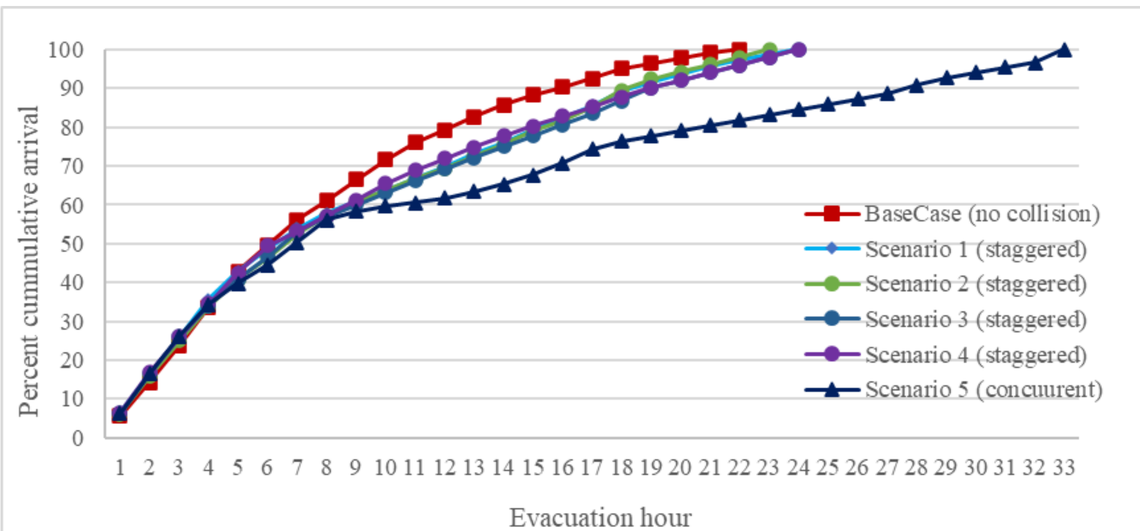


Figure 6-12 Percent cumulative completion of evacuation for base case, staggered and concurrent collision occurrence scenarios considering the non-removal of traffic disruptions

In the case of staggered disruptions, the traffic flow patterns are similar. It shows that although the congestion is higher in the mid-period of evacuation, the complete evacuation is achieved with a slight increase in evacuation time in the case of staggered disruptions. However, the results reveal that an evacuation with disruptions at different hotspots at the same time presents a critical condition that significantly prolong the evacuation. In the case of evacuation scenario 5 (concurrent), the evacuation is completed in 33 hours, which is 11 hours higher compared to a base case scenario. The results suggest that evacuation modelling without considering collision-related disruptions may significantly underestimate the network clearance time. Moreover, due to road damages by a flood of 3.9m water level in the same network, a complete evacuation required an additional 1 hour (Alam et al. 2018). Meanwhile, due to collision-related disruptions, it takes an additional 11 hours compared to the base case scenario. Traffic congestion is found significantly higher in the case of scenario 5 as reflected in the flattened and deviated traffic flow line in **Figure 6-12**. The variation in clearance time across the Halifax Peninsula zones under the concurrent collision occurrence scenario is shown in **Figure B – 5** of **Appendix B**.

6.7.2.2 Evacuation Traffic Congestion Analysis

Queue length

This study investigates traffic queue propagation due to collisions at hotspots in scenario 5 (**Figure 6-13**).

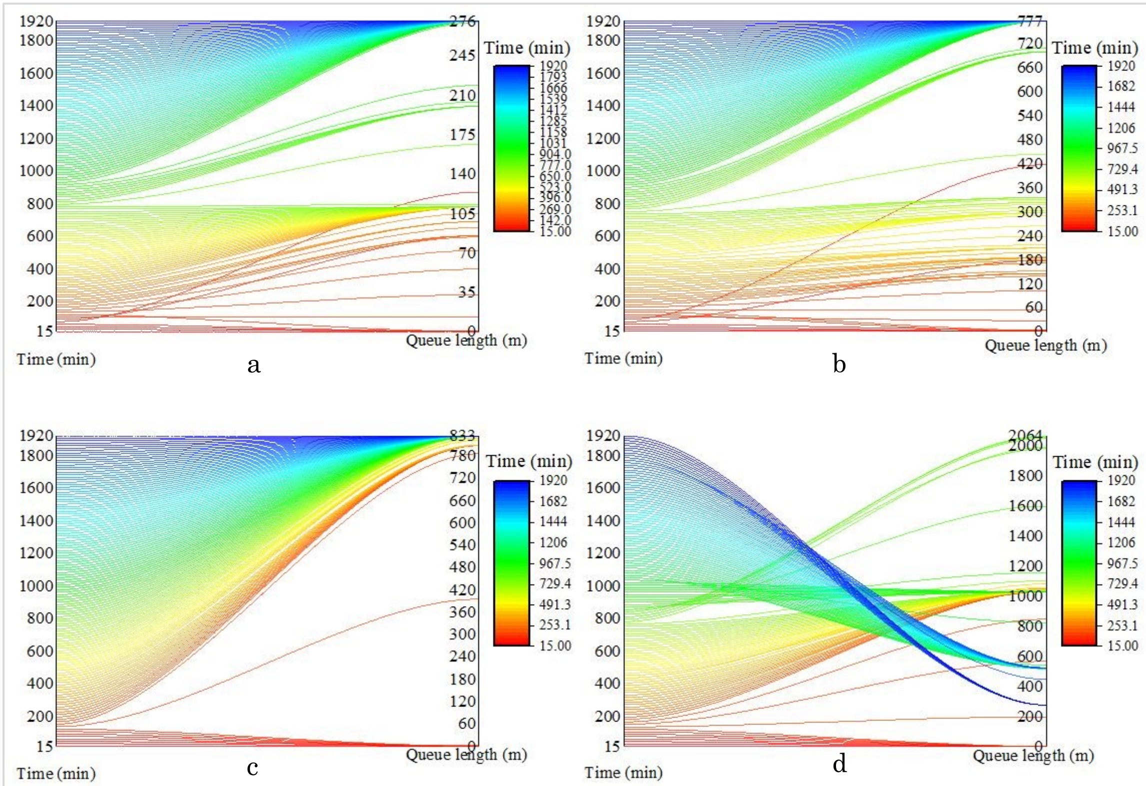


Figure 6-13 Queue propagation due to a collision at (a) location 1: Highway (b) location 1: Highway's ramp (c) location 3: Arterial Street, and (d) location 10: Downtown Street

Figure 6-13 presents the queue length at different times of the evacuation period at hotspots 'location 1', 'location 3', and 'location 10'. The simulation results suggest that the hotspots' traffic queues range from 0.28 km to 2.06 km depending on their locations in the study area. **Figure 6-13a** and **Figure 6-13b** show that traffic queue length increases along a highway and one of its ramps with the continuation of evacuation time due to a collision on the exit point (location 1) of the highway. The queue length on this highway reaches to a maximum value of 0.78 km at the 15th hour of evacuation. A collision on an arterial street (e.g., location 3) causes relatively higher congestion with respect to that of location 1. The reason is that this is a major connection between the city center and exits and therefore, anticipates a large traffic volume from the downtown and other parts of the area. This is also the reason for the queue being at peak at this location immediately after a collision occurred as shown in **Figure 6-13c.**

In the case of a collision at downtown street (location 10), queue starts to increase sharply right after the incident takes place until the 15th hour of evacuation. In the latter period, a decrease in traffic demand and a continuous evacuation through exit 4 (see **Figure 6-3** for exit locations) reduces the queue length at this location.

6.7.2.3 Corridor Traffic Congestion Analysis

This study further investigates traffic congestion along five major corridors as shown in **Figure 6-3**, where corridor 1 contains the hotspot 'location 1' at the end and starts from around hotspots 'location 3' and 'location 7'. Corridor 2 does not include any hotspot, while corridor 3 passes through hotspot 'location 5'. Corridor 4 passes through hotspot 'location 3' and corridor 5 contains hotspot 'location 10'. **Figure 6-14** illustrates the density (vehicles/km) along different corridors over the evacuation times for base case scenario and scenario 5 (concurrent disruptions).

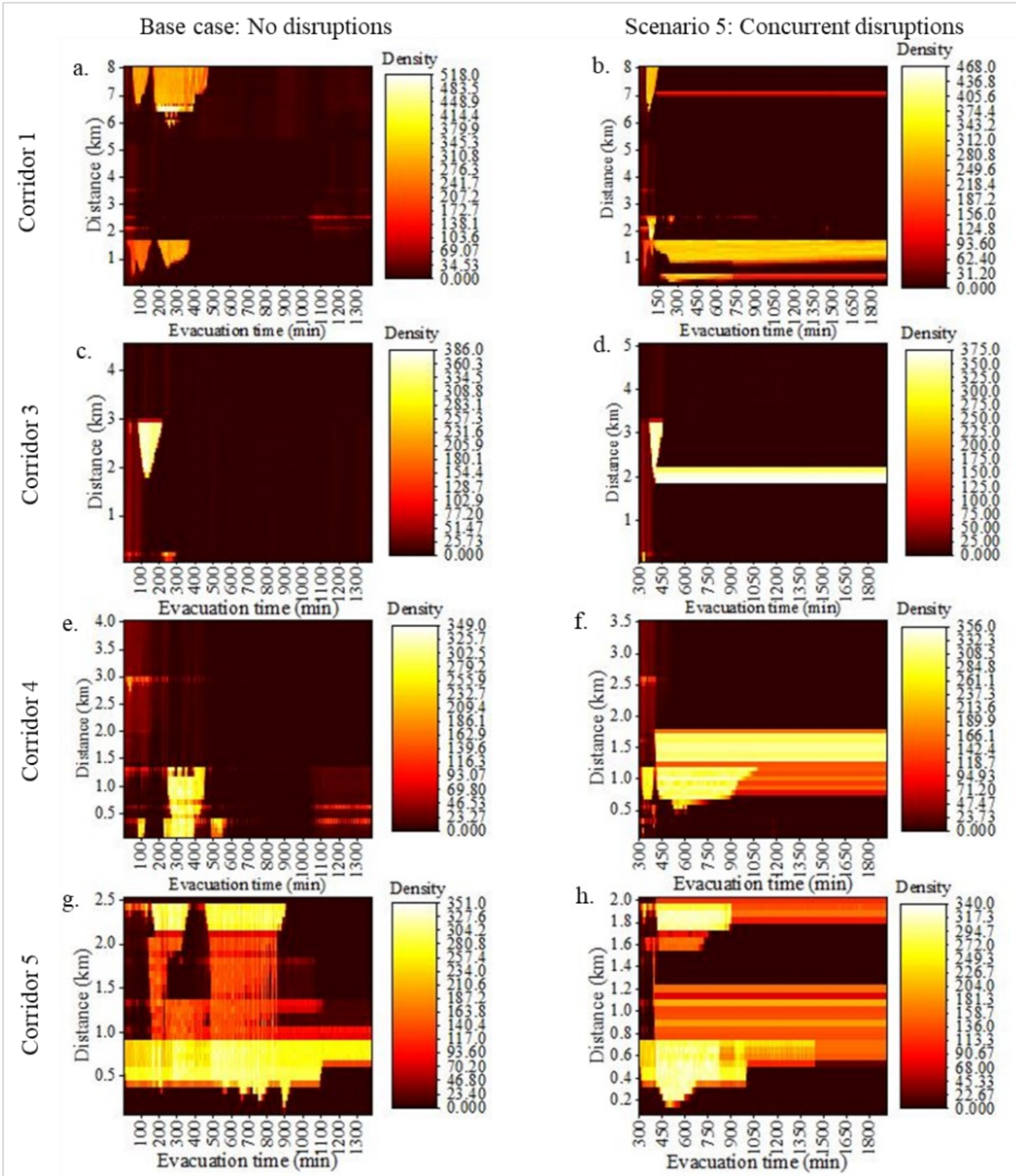


Figure 6-14 Traffic congestion measurements along different corridors resulting from vehicle collisions at hotspots in the Halifax Peninsula

Density of a corridor is found higher if the corridor experiences a collision at a hotspot. A higher density value indicates a higher degree of congestion. The results reveal that at the start and end of the corridor 1, traffic congestion is constantly higher for the entire evacuation period due to a collision at hotspots 'location 1' and 'location 3' (**Figure 6-14b**). Corridor 2 does not contain any hotspot and is not shown in **Figure 6-14**, which anticipates a higher traffic volume resulting from disruptions in scenario 5 when vehicles bypass the hotspots taking this corridor. Corridor 3 includes a collision at location 5, which causes sustained high congestion along this corridor (**Figure 6-14d**). Corridors 4 and 5 anticipate significant traffic congestion at their tails located in the downtown in the base case scenario. The existing level of congestion is aggravated due to the collision related disruptions at location 10 in scenario 5 as shown in **Figure 6-14f** and **Figure 6-14h**.

6.7.2.4 Zonal Traffic Congestion Analysis

This study examines changes in the travel time of fifty-six traffic analysis zones due to simultaneous occurrence of collisions at different hotspots within the study area. The study compares the influence of a collision event to the travel time of TAZs located within a 3-km radius of different collision locations. Broadly, the hotspots identified include highway exit, arterial street, and downtown street. **Figure 6-15** presents a box plot of travel time changes in TAZs due to collisions that occurred at these three location types.

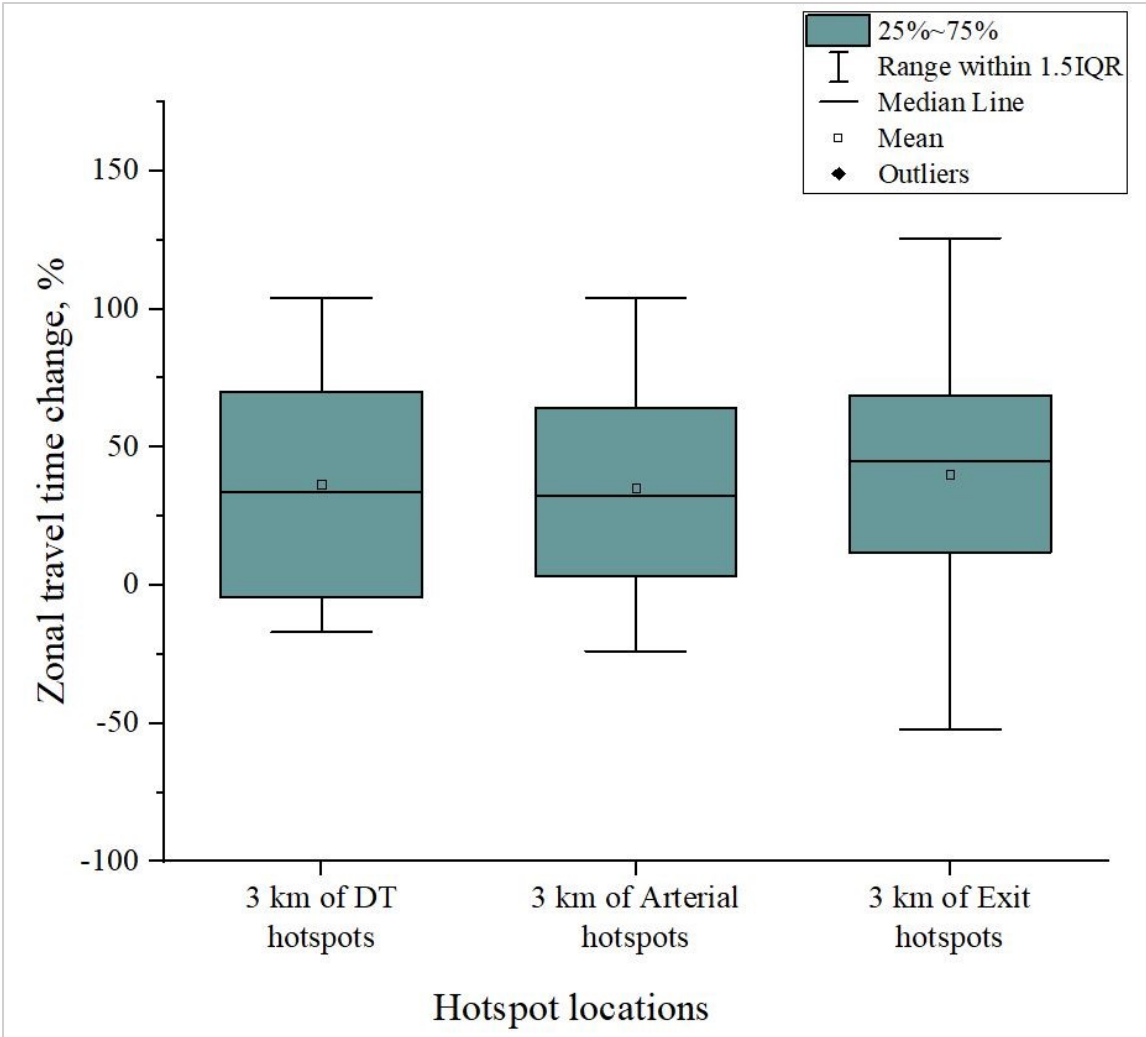


Figure 6-15 A box plot of travel time changes in traffic analysis zones due to the collisions occurrence at downtown street, arterial street, and highway exit

The results suggest that TAZs located within 3-km of downtown and arterial street hotspots anticipate a similar pattern of travel time changes and variability (represented by the bar width and median point in **Figure 6-15**). On the contrary, average travel time changes is higher in the case of TAZs within 3-km of exit hotspots. The top and bottom longer whisker for TAZs located 3-km of the exit hotspot demonstrate a higher variability in travel time gains or losses. The reason is that the evacuees of these TAZs adjust their exit choices due to the closure of their intended exit resulting from a vehicle collision. The alternative exit choices include either nearby exits if accessible or a distant exit across the city. Traveling to nearby and distant exits gives a rise to the variability in travel time. The results highlight the significance of suitable alternative exits when any unexpected closure of a particular exit occurs. In addition, a collision elsewhere within a city center would expect to have severe impacts on the evacuation traffic flows. Based on the result analysis and discussions, this study can inform policies to identify alternative routes to substitute exits if a collision where to occur.

6.8 Conclusions

This chapter presented a framework of traffic evacuation microsimulation modelling that includes a probabilistic model to identify collision hotspots for the implementation into a mass evacuation testing and evaluation. The study developed an enhanced probabilistic model following a combined Bayes theory and Monte Carlo simulation approach to predict collision hotspots using a rich Nova Scotia Collision Record Database. One of the unique features of this study is that it develops and tests contrasting evacuation scenarios considering uncertain network disruptions within the traffic evacuation microsimulation model.

The proposed framework is implemented to test and evaluate a case study in Halifax, Canada. Bayes theory analysis identified 128 potential collision locations in the study area among which, the Monte Carlo simulation approach identified five hotspots that impact the traffic movements within the evacuation area. A base case scenario without any collision disruptions, four scenarios with staggered collision disruptions, and a scenario with concurrent collision disruptions were evaluated in terms of overall evacuation performance, travel time changes and five corridor performances. The assessment of overall evacuation performance revealed that scenario 5, in which all the collisions are assumed to occur concurrently, presented the worst-case scenario in the Halifax transport network. In this scenario, it required an additional 11 hours for a complete evacuation in comparison to the base case scenario. Further simulation results suggest that in the case of staggered collision disruptions, the minimum evacuation time is 23 hours if the collision disruption is removed in 2 hours or less. The maximum evacuation time is 24 hours with no removal of disruption or with removal after 2 hours in case of staggered collision scenario. The evacuation time turns out to vary within 23-31 hours if the disruption is removed within 2-24 hours for a concurrent collision occurrence scenario. Although, regional level changes on evacuation performances are not evident in the case of staggered collision occurrence, individual level impacts refer to a reduced travel time if the collision is removed. The evaluation of the corridor performance suggests that corridors that pass across downtown area anticipate significant collision-related impacts and congestions compared to others. An interesting finding is that corridor 2 plays an important role as a backup link, which anticipates diverted traffic volume in all disrupted scenarios. The results of this research provide insights into the network's vulnerability to risks inherent to traffic operations during an evacuation. The results also help identifying hotspots to address uncertain network disruptions and backup links/corridors to accommodate the diverted evacuation traffic in the network. The estimation of the potential impacts of vehicle collision-related disruptions on the total network clearance time and percent completion of the evacuation are also conveyed through this research. This research acknowledges that the collision frequency may rise due to stress and rushing during evacuation as occurred in the case of Hurricane Irene and Sandy evacuation. The model developed in this study is flexible to take that into account for and evaluate more disruption scenarios in future.

This study contributes to the coupling of collision research methods and traffic microsimulation modelling to address uncertain network disruptions during an evacuation in the transport network. The study provides an extensive analysis of different evacuation scenarios considering staggered and concurrent disruptions. Traffic evacuation microsimulation model developed in this thesis demonstrates the capability to address natural disaster as well as traffic operation related complexities in assessing evacuation scenarios. The model provides an upper limit of evacuation times which is 33 hours considering vehicle collision related network disruptions; 22 hours being the lower limit of evacuation time for the Halifax Peninsula when considering an evacuation with no disruption risks accommodated. The results indicate that 22-33 hours is significantly a long clearance time which warrants an effective pre-evacuation planning with adequate identification of the most vulnerable population and the development of possible evacuation countermeasures to conduct an efficient evacuation. Therefore, the rest chapters will focus on the vulnerability assessment and countermeasure developments utilizing the simulation outputs, and other sources of data.

Chapter 7

Vulnerability Assessment for a Mass Evacuation[4]

7.1 Introduction

This chapter leverages several components developed in the earlier chapters to inform the development of a vulnerability assessment modelling framework. Mass evacuation from a disaster-prone area to shelters has the potential to prolong the evacuation procedure during an emergency. Spatial zones that are at relatively a higher risk of natural disaster impacts and/or exposed to other vulnerabilities can be prioritized for evacuation. In current practice, zonal vulnerability is determined based on geophysical conditions that yield seriousness of risk and the social systems which refer to variations of risk (Kar and Hodgson, 2012; Schmidtlein, 2011). Most studies (Fernandez and Lutz, 2010; Wood et al., 2010) are static in nature and perform independent processes. However, vulnerability in disaster-prone areas is dynamic and often stems from mobility complexity, including flood flows, and traffic movements. Vulnerability assessment taking an integrated approach is not well explored with respect to geophysical condition, social risk, and traffic movement; even though, this type of analysis would offer better understanding to develop effective evacuation plans.

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[4] This chapter is partially derived from the following peer-reviewed journal paper:

- Alam, M. J., and Habib, M. A. (2019). Vulnerability Assessment during Mass Evacuation: An Integrated Microsimulation-Based Evacuation Modelling Approach. *Transportation Research Record*, 2673 (10), 225-238

How quickly the population of a zone can be evacuated safely before a disaster impacts, is a critical aspect in emergency evacuation planning. The condition of a transportation network over the affected region, traffic flow pattern, network supply and evacuation demand determine the complexity of an evacuation operation from a traffic management point of view. For example, lower network capacity poses a higher risk for mass evacuation of an area. Simultaneously, meeting the transportation needs of the vulnerable population such as carless population group could elevate the complexity of an evacuation operation. The main challenge in estimating evacuation risk is that observation of an evacuation event is often not feasible, particularly in coastal areas, resulting in insufficient knowledge of traffic flow pattern. Additionally, difficulties in measuring social vulnerability for coastal areas results from a lack of understanding of demographic changes and key household decisions affecting land use patterns. Therefore, it is necessary to develop a sequential modelling system that includes modelling elements of long-term changes: such as residential mobility decisions, vehicle ownership, flood risks, traffic movement, and vulnerability assessment. Particularly, combining integrated urban systems and traffic microsimulation models is advantageous as the forecasted results can be used to develop evacuation plans for any number of years to come. Therefore, a modular-based evacuation modelling framework is of paramount importance for a reliable estimate of the vulnerability.

The objective of this study is to conduct a comprehensive vulnerability assessment of traffic analysis zones while combining a Bayesian Belief Network-based vulnerability assessment model with different multilayer modules. The modules include (i) an integrated urban systems model that simulates land use variations and vehicle ownership over the course of time, (ii) a flood risk model that predicts flood severity and flood-related network disruptions, and (iii) a dynamic traffic assignment (DTA)-based microsimulation model that provides network supply constraints. Integrated urban systems model simulates long-term changes in demographic characteristics, particularly, residential location choices and vehicle transaction decisions within a long-term simulator. The results of the long-term simulator can then be used to determine the social vulnerability. The flood risk model informs flood severity and network disruptions for developing evacuation scenarios. Evacuation scenarios are simulated within the microsimulation model to measure mobility risk during an emergency. The proposed integrated modelling framework is empirically tested for assessing the vulnerability of areas identified as traffic analysis zones (TAZs) on the Halifax Peninsula, Canada. For the vulnerability assessment model, this study proposes a novel approach utilizing a Bayesian Belief Network (BBN) that uses information obtained from the integrated urban systems model, flood risk model, and traffic microsimulation model. It uses an Analytical Hierarchy Process (AHP) to determine the weighting factors of the vulnerability variables of interests. The vulnerability assessment model informs different evacuation planning scenarios for an empirical application.

7.2 Literature Review

The vulnerability of an area is measured by the extent of the potential impact and the degree of exposure, susceptibility, and resilience of that area (Balica et al., 2012; Fuch et al., 2011). Several methods are proposed in existing literature to estimate vulnerability in relation to natural disasters and/or socio-economic diversity. Fernandez and Lutz (2010) applied a multi-criteria decision making-analysis to develop a flood hazard zoning system for an urban area. This study modelled disaster impacts over an area and addressed the natural system component for vulnerability assessment. Rygel et al. (2006) explored how various groups of people are affected differently by a natural disaster based on socio-demographic heterogeneity. The authors assessed the vulnerability as a measure of resistance capacity of that area. They used a principal component analysis to develop a socio-demographic index for urban flood hazard. A study by Balica and Wright (2009) also examined flood-related vulnerability by considering geological exposure and the social, economic, and institutional status of an area. The analysis was conducted at the city level; however, vulnerability may vary spatially across the city at finer level (e.g., TAZ). Abovementioned studies are static in nature and utilized cross-sectional information. On the other hand, integrated urban systems model dynamically simulates different longer-term decision processes. It captures the changes in the neighborhood composition in terms of population, socioeconomic, and demographic changes, and auto ownership; however, these aspects have often been overlooked for vulnerability assessment modelling. Chakraborty et al. (2005) studied evacuation risk by considering social and accessibility to resource attributes. Hsu and Peeta (2014) considered natural hazards and network supply attributes to determine emergency planning zones. Urban systems model can enhance the reliability of the vulnerability assessment given that the vulnerability can be measured by the degree to which societies or individuals are potentially threatened. For example, a marginalized group of people is likely to suffer from an evacuation. Over the past several years, transportation researchers have been attempting to design and evolve land use modelling systems. For example, 'UrbanSim' (Waddell et al., 2003), a macroeconomic model of location choice of households and firms. This executes macroeconomic and travel demand models, household and employment mobility and location choice models to forecast the way that demographics change, and travel conditions evolve in parallel. Another integrated urban modelling system named 'Integrated Land Use, Transportation, Environment (ILUTE)' is used to predict land development, location choice of households, firms, workers, vehicle ownership of households and travel conditions (Miller and Salvini, 1998). Similarly, an integrated urban model named 'Integrated Transport Land Use and Energy (iTLE)' (Fatmi and Habib, 2018; Fatmi et al.,

2017) assumes that individuals and households are agent and parcels are the objects. The iTLE evaluates how people's location choice behavior and vehicle ownership evolves at different life-stages. Such long-term simulators can anticipate residential location choice, vehicle ownership and travel behavior of households over time. These life-stage decisions are determinants of the vulnerability of a group of people or locality during a natural disaster and related evacuation phenomena.

Another major concern is that network disruption is hardly considered in evacuation operation studies. Any disruptions to network can significantly impact evacuation times which is a critical determinant to assess the mobility vulnerability of an area. Moreover, existing network disruption studies focus on small scale areas. For example, Dehghanisanij et al. (2013) determined the efficiency of disrupted and undisrupted network of fourteen links. The authors conducted a condition-based analysis and estimated a ratio regarding transport-related measures, such as vehicle miles travelled in disrupted and undisrupted networks. Tang and Huang (2018) assessed connectivity in terms of degree of road blockage for a network of nine major roads and eight intersections considering a seismic activity. However, to consider network disruptions for a mass evacuation, it warrants traffic modelling of the entire network that dynamically evolves at a finer grain time step. Particularly, a dynamic traffic assignment-based microsimulation model developed in this thesis is of paramount importance to capture routing policies and congestion propagation. Few studies (Yin et al., 2014; Ukkusuri et al., 2017) took integrated approaches which include models for evacuation decisions and transportation choice dimensions, i.e., departure time and route choice. These studies combined activity-based models with traffic simulation models. One of our earlier contributions (Alam et al., 2018) also developed a sequential modelling framework that includes a flood risk model, a regional transport network model and a traffic microsimulation model. However, vulnerability assessment requests the distribution of population in different time periods, which is absent within these sequential evacuation modelling frameworks. This research aims to fill the gap by combining an integrated urban systems model and the sequential modelling approach (Alam et al., 2018) that offers reliable information on the condition of flood flows, demographic changes, network disruptions, and traffic patterns for the vulnerability assessment.

Many studies (Wood et al., 2010; Balica et al., 2012; Balica and Wright, 2009; Chakraborty et al., 2005) contributed to the research of vulnerability assessment modelling. Methods used in these studies include indicator-based flood vulnerability assessment, construction of GIS-based composite vulnerability index, estimation of general flood vulnerability index using simple averaging method, and GIS-based risk score assignment. The limitation of these methods is that they cannot capture the uncertain features of the vulnerability. They are unable to address the causal relationships among various elements of the vulnerability. Moreover, they generally perform a single-directional vulnerability assessment at a time. However, the BBN modelling can compute posterior probability of unobserved variables depending on the variables that are observed. It can capture multi-directional causal relationships obtained from the integrated modelling systems and estimate various vulnerabilities in a single framework to determine the overall risk of the system. The Bayesian Belief Network modelling has recently been evolved and applied in the field of infrastructure system for risk and reliability analysis (Hosseini and Barker, 2016). However, its application in the transportation sector has not yet been explored. Moreover, weighting factors of variables of interests can be used within the BBN modelling framework to consider the relative influence of variables on overall vulnerability (Mimovic et al., 2015). This study couples Analytical Hierarchy Process with the BBN model to identify the riskiest zones during an evacuation of Halifax.

7.3 Methodology

7.3.1 Vulnerability Assessment Modelling Framework

This study develops a modular-based evacuation modelling framework for the vulnerability assessment in the context of a mass evacuation. The vulnerability assessment offers an opportunity to identify risky zones. To accomplish this task, the study develops a Bayesian Belief Network-based vulnerability assessment model which is coupled with three components: (i) an integrated urban systems model, (ii) a flood risk model, and (iii) a DTA-based evacuation microsimulation model. The urban systems model includes a long-term simulator and a regional transport network model, as shown in **Figure 7-1**. The long-term simulator generates synthesized population and addresses residential location choice and vehicle transaction behavior over the life course of the households (Fatmi and Habib, 2018). The model micro simulates key household decisions for 15 years ranging from 2007-2021, using 2006 as the base year. This model examines how key life stage transitions evolve over time, which is an important determinant of the vulnerability assessment. This study uses the urban systems model results from 2016 to test the efficacy of the proposed framework. The regional transport network model estimates evacuation demand, which determines risk regarding logistical constraints, and populates traffic flow within the microsimulation model. A flood risk model informs both the vulnerability assessment and the microsimulation model about flood severity and network disruptions. Microsimulation of evacuation scenarios generates network supply constraints for the estimation of mobility vulnerability. Details of traffic microsimulation, and flood risk models can be found in Alam et al. (2018) and are included in Chapter 4. The regional transport network model is described in detail by Bela and Habib (2018).

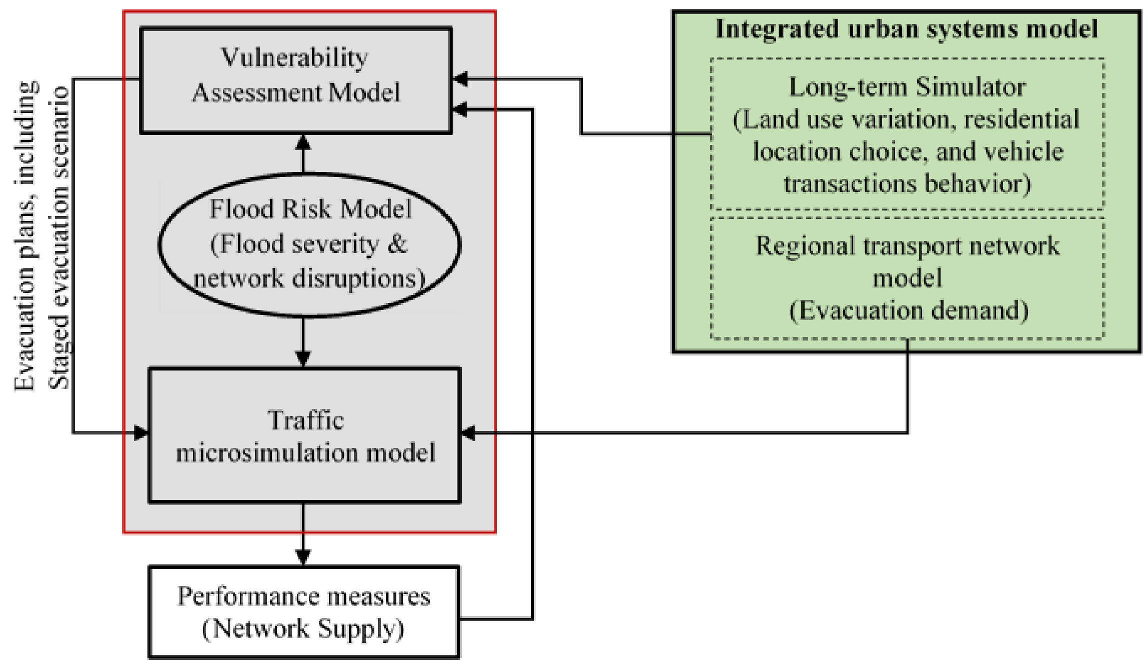

Figure 7-1 Modular-based vulnerability assessment modelling framework

This study adopts an integrated approach of Bayesian Belief Network modelling and Analytical Hierarchy Process to develop the vulnerability assessment framework. The study will examine the development of the vulnerability assessment model utilizing the inputs from the urban systems model, flood risk and traffic microsimulation model, as well as analyze the risk results that will be obtained from the application of the proposed framework.

7.3.1.1 Bayesian Belief Network Modelling Approach

This study has adopted a Bayesian Belief Network modelling approach, which is based on a Bayesian theorem. It essentially estimates the probability to measure the lack of knowledge regarding the occurrence or non-occurrence of an event. The study utilizes BN to compute posterior probability of unobserved variables depending on the evidence of observed variables. In this study, uncertain variables are presented as nodes and casual relationships between nodes or variables are depicted as an edge connecting two nodes. Conditional probability tables (CPT) are developed to determine the strength of relationships between variables. The BN that is developed in this study is a directed graph which does not allow any cycle in it.

For the vulnerability assessment, let's assume, a simple Bayesian Network seen in **Figure 7-2**, which includes a set of variables (e.g. v_1= no vehicle ownership, v_2 = presence of seniors in household, v_3= flood severity, v_4= clearance time, ……… v_n), $V = \{v_1, v_2, v_3 .... v_n\}$.

The relationships between variables are represented by edges from node v_i to v_j. For example, edge 1 from v_1 to v_4 provides the conditional probability $p(v_4 | v_1)$ indicating v_4 is dependent of the value of v_1. As the edge goes out from v_1 to v_4, v_1 is called parent node of v_4 and v_4 is called child node of v_1.

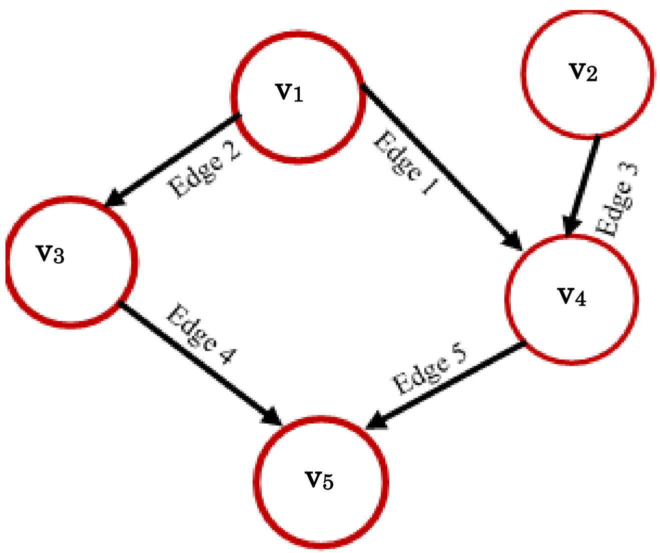

Figure 7-2 An example of BN incorporating five variables

Nodes which have no parent nodes are known as root nodes e.g. v_1 and v_2 , and nodes having parent nodes, but no child nodes are called leaf nodes, e.g. v_5. The rest are known as intermediate nodes (e.g. v_3 and v_4). Given the conditional probabilities (e.g. $v_4 | v_1$, $v_4 | v_2$), the full joint probability of BN for

n variables, $v_1, v_2, v_3 .... v_n$, can be estimated using the following equations:

$$p(v_1, v_2, v_3 .... v_n) = p(v_1 \mid v_2, v_3 .... v_n) p(v_2 \mid v_3, v_4 .... v_n) .... p(v_{n-1} \mid v_n) p(v_n) \\ = \prod_{k=1}^{n} p(v_k \mid v_{k+1} .... v_n) \tag{1}$$

However, each node is conditionally independent of its non-descendants, given its immediate parent nodes. In that case, equation 1, for full joint probability, can be transformed into the following equation where each node is conditioned over its parents.

$$p(v_1, v_2, v_3 .... v_n) = \prod_{k=1}^{n} p(v_k \mid (v^{v_k}_{parents,i}) \tag{2}$$

Where $v^{v_k}_{parents,i}$ is a set of all parent nodes of variable v_k

One of the notable features of the BBN model is that it can update belief of any variable by observing evidence of other variables. For example, the conditional probability of variable, v_1, given the evidence, $E = \{v_2, v_3 .... v_n\}$, can be calculated as follows:

$$p(v_1 \mid E) = \frac{p(v_1, v_2, v_3 .... v_n)}{p(v_2, v_3 .... v_n)} \tag{3}$$

Additionally, the relative importance of risks and the associated risk factors can be imported into Bayesian Belief Network to identify the most significant risk.

To determine the degrees of the impacts of vulnerability variables, this study has adopted an AHP (Hosseini and Barker, 2016) approach. The proposed approach uses a scale ranging from 1-9 (Saaty, 1980) to make judgment for pairwise comparison of the variables. To determine the potential inconsistency in judgment, a consistency ratio (CR) is estimated utilizing eigenvector method (Alonso and Lamata, 2005). First, a consistency index CI (used to measure the inconsistency of pairwise comparison) can be estimated using the following equation:

$$CI = \frac{\gamma_{\max} - \eta}{\eta - 1} \tag{4}$$

Where $\gamma_{\max}$ is the largest Eigen value in reciprocal matrix, and η is the number of rows or column. $\gamma_{\max}$ is always greater than or equal to η. Three conditions together represent an instance of complete consistency (Saaty, 1980), which includes:

(i) $x_{ij} * x_{jk} = x_{ik} \ (\forall i, j, k)$ (5)

(ii) $\gamma_{\max} = \eta$ (6)

(iii) $CI = 0$ (7)

Where x_{ij} represent the values in the comparison matrix. If there exists no absolute consistency in experts' judgments, then $\gamma_{\max} > \eta$ and the following equation of consistency ratio can be used:

$$CR = \frac{CI}{RI} \tag{8}$$

RI is the average value of CI for a random matrix. This random matrix can be obtained from Forman (Forman, 1990). A CR value greater than 0.1 requires revision of the judgment in the matrix because of inconsistent treatment of a factor rating. The vulnerability of areas is then determined utilizing the proposed modelling approach in light of information obtained from an integrated urban systems model, a flood risk model and a traffic microsimulation model.

7.4 Empirical Application of the Proposed Framework

7.4.1 Determination of Variables Affecting Vulnerability

In order to develop a set of variables within the BBN modelling framework for vulnerability assessment, this study relies on earlier studies that specifically focused on identifying factors affecting vulnerability. In total, 29 variables that affects social vulnerability are analyzed and are made concise into six variables for the vulnerability assessment during an evacuation. A brief review of variables can be found in Wood et al. (2010). The socio-demographic variables identified in this study are presence of female, children, and seniors in a household, household size and income, and no vehicle ownership. Extra safety awareness is perceived if female and children are present in household during an evacuation (Smith and McCarty, 2009). Females are more vulnerable than men because of their role as caregiver to children and seniors who need assistance, which prevent females from seeking safe places during an evacuation. Presence of seniors decreases evacuation rates as physical impairments and medical conditions limit the mobility of older persons, which enables a higher risk household. Larger households experience high logistic constraints. Another key factor for assessing vulnerability is income, which affects vehicle ownership of a household. 'No vehicle ownership' raises concern regarding transportation arrangements to evacuate the transit – dependent population. Flood severity and distance of a zone to the flood source are important measures for assessing the degree of vulnerability of that area (Smith and McCarty, 2009). The flood risk model used in this study revealed that a higher flood severity and a zone's proximity to a flood source can cause higher inundation of the area and network links. Moreover, house type is another crucial factor that determines the susceptibility of an area to natural disasters. Due to the nature of construction, mobile houses are more likely to suffer from flood or storm damages (Smith et al., 2006). This study uses clearance time, demand density and zone to exit distance to determine the degree of evacuation complexity. For example, exit closure is likely to increase clearance time and large population size adds difficulty in evacuation due to the requirements of extensive logistic support (Hsu and Peeta, 2014). Given the factors and causal relationships of the variables described above, the proposed BBN modelling framework is presented in **Figure 7-3** followed by the estimation of the variables.

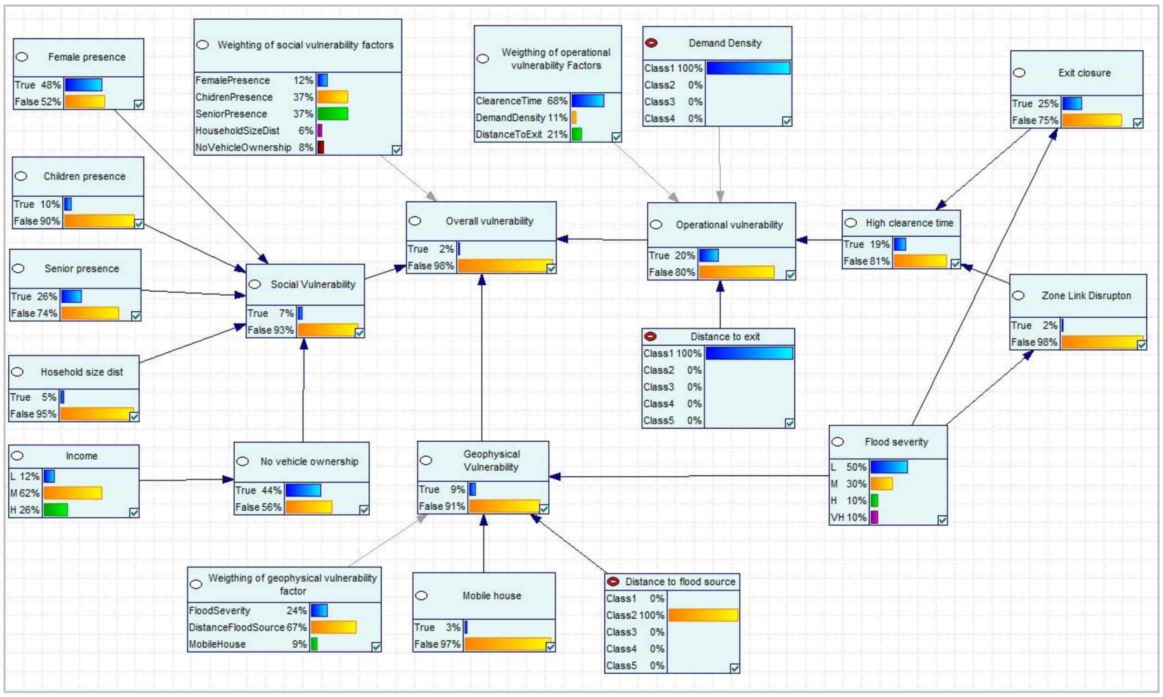

Figure 7-3 Proposed BBN model for vulnerability assessment of the Halifax Peninsula

7.4.2 Estimation of the Variables for BBN Model

7.4.2.1 Estimation of the Social Vulnerability Variables through Urban Systems Modelling

The long-term simulator used in this study yields socio-demographic variables identified in the previous section for the period of fifteen years (from 2007 to 2021). This study uses the urban systems model results to assess the vulnerability for the year of 2011. In this study, children presence is 'True' if the age of any household member is < 18 and 'False' if the age is > 18. In this case, the age group that is less than 18 represents young adult and children who are deemed to be vulnerable and dependent on others for evacuation. Similarly, for seniors, 'True' holds if the age is > 65 and 'False' if the age is < 65. The number of females, children, and seniors are predicted for each TAZ of the Halifax Peninsula utilizing the urban systems model. Then, based on the total population in the zone, % female, % children, and % seniors are estimated. In relation to different income categories, % household having zero vehicle in a zone is also estimated using the similar technique. According to a study (Bongaarts, 2001) by the United Nations, a household with five members or more can be considered as a large household. The total number of individuals in a household is determined by carrying the IDs of all household members under a unique household ID in the simulator. Based on the number of members in the households, the total number of large households in a zone is estimated. A 'True' state is used in the BBN model if the number of household members is greater than or equal to 5 and 'False' if it is less than 5.

7.4.2.2 Estimation of the Geophysical Vulnerability Variables through Flood Risk Modelling

The extent of flooding over the Halifax region is determined utilizing a flood risk model described in Chapter 4. The flood risk model generates flood layers based on Hurricane Juan and overlays them with Nova Scotia road network to simulate the extent of the inundation over the region. The flood risk model contributes to this study with three flood severity scenarios and identifies network link disruptions in percent of the total link length. Moreover, the model informs if exit closures occur for each flood scenario. Flood severity is measured based on water level such as Low (2.9m water level), Medium (3.9m water level), and High (7.9m water level). The information obtained from the flood risk model is used to determine posterior probabilities of 'exit closure' and ‘zone-specific link disruption’ given their parent node ‘flood severity’. Boolean expression is used in this case. For example, based on flood risk model results, if the flood severity is high, an exit closure is certain which is represented by a value of 1 in the BBN model. In **Table 7-1**, several cases are shown where Boolean expression is used. Two states named ‘True’ and ‘False’ are used where ‘True’ states the likelihood of occurrence and ‘False’ states the non-occurrence of a candidate event.

Table 7-1 Sample Boolean Expression Used to Determine the Posterior Probabilities for Different Vulnerability Variables

Variable	Example of expression & description
Zone-specific link disruption	If (flood severity = VH = 15.0m water level, ‘True’, ‘False’) - if flood severity is very high with certain likelihood, disruption to links of a zone is also true at certain degree of belief
Exit closure	If (flood severity = High = 7.9m water level, ‘True’, False’) - if flood severity is high with certain likelihood, exit closure is true with a certain degree of belief
Clearance time	If (zone link disruption = True, exit closure = True, ‘True’, ‘False’) - if zone link disruption and exit closure occur, clearance time is greater than 1.0 hour with certain degree of belief

Geographic location of a zone is also important to assess geophysical vulnerability. The location of a zone with respect to exit and flood source are determined using the 2012 Halifax Geodatabase. Distance of any TAZ to a flood source is inversely related to the degree of impacts that zone experiences. This study introduces five classes of distances for the BBN model, such as class 1 if distance is < 100m, class 2 if distance is > 100m and <300m, class 3 if distance is >300m and <500m, class 4 if distance is >500m and <1000m, and class 5 if distance is >1000m, to measure the geophysical vulnerability. Distance is considered as a deterministic variable for BBN modelling.

7.4.2.3 Estimation of the Mobility Vulnerability Variables through Evacuation Microsimulation Modelling

To obtain the zonal clearance time, a microsimulation model developed by Alam et al. (2018) is updated and utilized to simulate evacuation scenarios. The 'clearance time' required to evacuate each zone on the Peninsula is determined through the simulation. A higher clearance time poses higher level of risk to safely evacuate the residents (i.e. mobility vulnerability). The updated traffic evacuation microsimulation model of the Halifax Peninsula has five entry-exit points for evacuation. The exits include two bridges, two highways and a roundabout. The model treats areas as traffic analysis zone (TAZ) and simulates the evacuation of 56 TAZs on the Peninsula. The zoning system used in this study is in alignment with the zoning system of the Halifax transport network model developed by Bela and Habib (2018). The Halifax transport network model is utilized to estimate the evacuation demand on the Peninsula. After the simulation, the total time required to evacuate each TAZ is recorded. Boolean expression is used to obtain the posterior probability of 'clearance time' given its parent nodes, 'zone link disruption' and 'exit closure' (see **Table 7-1**). A state 'True' is used for BBN modelling if the clearance time is 'High', meaning clearance time is > 1 hour, otherwise, 'False' is used.

Moreover, greater distance to exit and higher demand density also elevate the mobility complexity during an evacuation. In this study, distance to exit is indexed as class 1 if distance is < 1.0 km, class 2 if distance is >1.0 km and <2.0 km, class 3 if distance is >2.0 km and <3.0 km, class 4 if distance is >3.0 km and <4.0 km, and class 5 if distance is >4.0 km. Demand density is also normalized into five classes such as class 1: 0-0.2, class 2: 0.2-0.4, class 3: 0.4-0.6, class 4: 0.6-0.8, and class 5: 0.8-1.0. The probabilities for nodes 'social vulnerability', 'geophysical vulnerability' and 'mobility vulnerability' in the BN are determined by the weighted sum of probabilities of their 'parent nodes'. A label type node representing the weights of each variable is introduced in the

BN. Such weights can be obtained from engineering judgment and/or expert knowledge using any of the different decision analysis techniques. This study combines AHP with BBN to incorporate weights for each variable in the Bayesian Network-based vulnerability assessment model. The conditional probability table for the node of composite vulnerability is derived by weighted sum of social, geophysical and mobility vulnerability and then composite vulnerability is measured.

7.4.3 Weighting of Variables for BBN Model

This study utilizes AHP to determine the weighting factors for all variables of three vulnerabilities. For demonstration purpose, the weighting of variables affecting social vulnerability is presented in **Table 7-2**. For social vulnerability, AHP follows a four-step approach and V1 stands for 'female presence', V2 for 'children presence', V3 for 'senior presence', V4 for 'large household', and V5 for 'no vehicle ownership'. First step involves pairwise comparison of factors informed by the local experts in the same field. Moreover, insights from the literature review presented in this chapter have assisted in understanding the relative significance of the factors. All the resulting weighting factors of variables of three vulnerabilities with the consistency ratio are presented in **Table 7-3**.

Table 7-2 Four-step AHP for Weighting Factors of Five Variables Affecting Social Vulnerability

Step 1: Pairwise comparison of variables based on scale 1-9

	V1	V2	V3	V4	V5
V1	1	1/3	1/3	3	1
V2	3	1	1	7	5
V3	3	1	1	7	5
V4	1/3	1/7	1/7	1	1
V5	1	1/5	1/5	1	1
Sum	8.333	2.676	2.676	19	13

Step 2: Normalization of the matrix in step 1 and setting priority by taking average of each row

	V1	V2	V3	V4	V5	Priority
V1	0.120	0.124	0.124	0.158	0.077	0.121
V2	0.360	0.374	0.374	0.368	0.385	0.372
V3	0.360	0.374	0.374	0.368	0.385	0.372
V4	0.040	0.053	0.053	0.053	0.077	0.055
V5	0.120	0.075	0.075	0.053	0.077	0.080

Step 3: Weighted Sum Estimation by multiplying criteria weight with each cell in step 1 and taking sum of each row

	V1	V2	V3	V4	V5	Weighted Sum
Criteria weight	0.121	0.372	0.372	0.055	0.080	
V1	0.121	0.124	0.124	0.166	0.080	0.614
V2	0.362	0.372	0.372	0.387	0.399	1.892
V3	0.362	0.372	0.372	0.387	0.399	1.892
V4	0.040	0.053	0.053	0.055	0.080	0.282
V5	0.121	0.074	0.074	0.055	0.080	0.405

Step 4: Calculate maximum Eigen value and CR

Weighted sum	For Priority in col 2	For Priority in col 3	For Priority in col 4	For Priority in col 5	For Priority in col 6	Average Eigen value
0.614	0.121	4.957	4.957	3.704	7.696	4.676
1.892	5.224	5.086	5.086	4.891	4.742	5.072
1.892	5.256	5.064	5.064	5.136	4.920	5.130
0.282	7.007	5.294	5.294	5.096	3.530	5.673
0.405	3.351	5.438	5.438	7.320	5.070	5.387
					Maximum Eigen value	5.188

Number of variables, n = 5, and RI = 1.12

CI = (5.188-5)/(5-1) = 0.047

CR = 0.047/1.12 = 0.042

Table 7-3 AHP-based Weight Assignment to Variables of Different Vulnerabilities and Consistency Ratios

Vulnerability Class	Variables	Weight Assigned	Consistency Ratio
Social Vulnerability	Female presence	0.121	0.042<0.1
	Children presence	0.372	
	Senior presence	0.372	
	Large household	0.055	
	No vehicle ownership	0.080	
Geophysical Vulnerability	Flood severity	0.24	0.01<0.1
	Distance to flood source	0.67	
	Mobile house	0.08	
Mobility Vulnerability	High clearance time	0.68	0.05<0.1
	Demand density	0.11	
	Distance to exit	0.21	

7.5 Results and Discussions

7.5.1 Vulnerability Assessment Results

This study develops a composite vulnerability as well as social, geophysical, and mobility vulnerability. It identifies risky zones based on the model results as presented in **Figure 7-4**. The results reveal that vulnerable zones are found to be sporadically located at the North- and South-end of the Peninsula, the downtown core, the Quinpool and Mumford area. **Figure 7-4a** shows that the North-end of the Peninsula is significantly vulnerable in terms of composite vulnerability. The composite vulnerability of this end is dominated by social and mobility vulnerability as seen in **Figure 7-4b** and **Figure 7-4d** respectively. Similarly, several zones located by Quinpool and Mumford road are low-income areas and found significantly socially vulnerable (**Figure 7-4b**). Mobility vulnerability of these zones is also observed to be significant (**Figure 7-4d**). Social vulnerability is likely to be concentrated at the downtown core and two ends of the Peninsula. The vulnerability results suggest that zones that are socially vulnerable are a result of the presence of females and seniors in those zones.

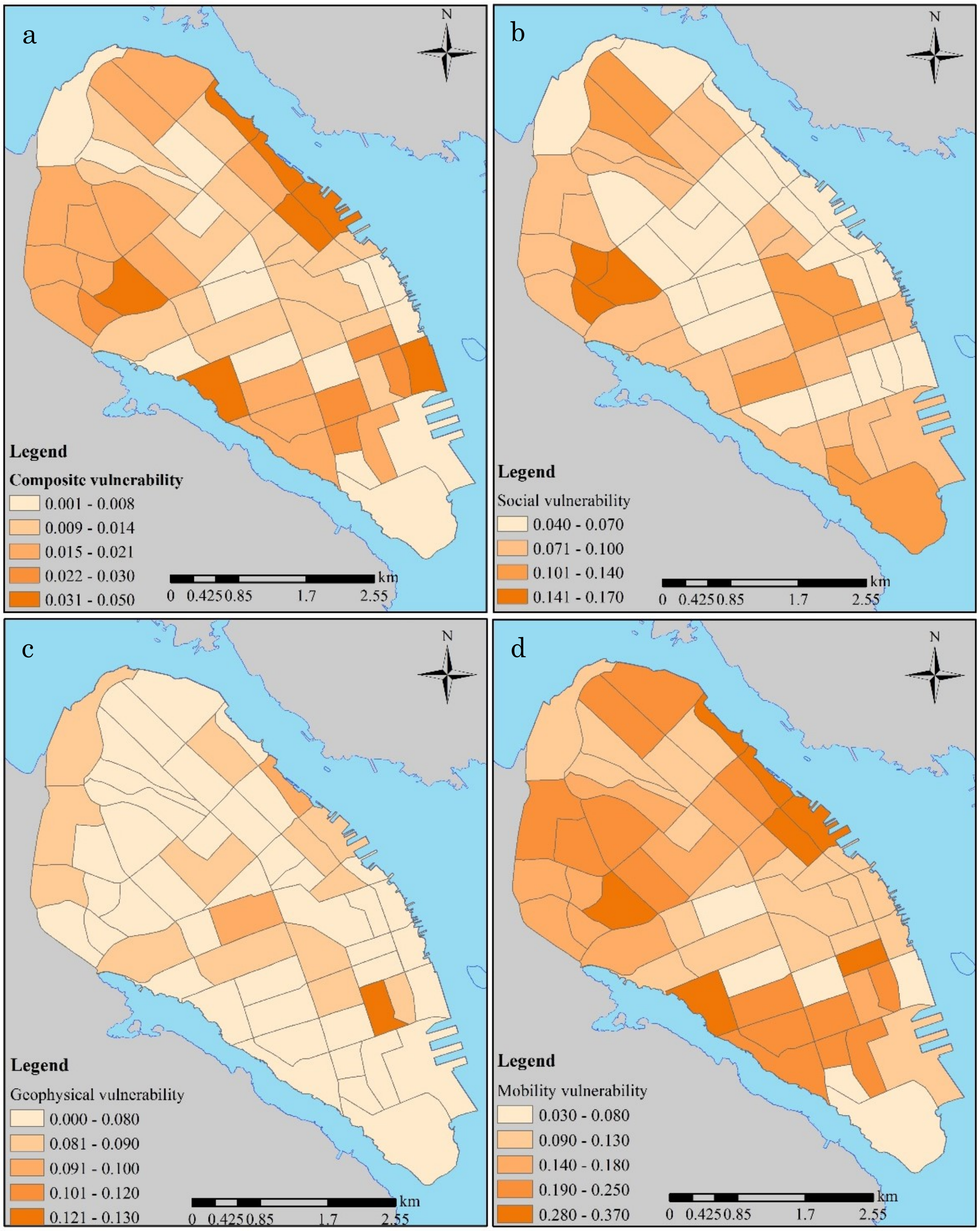

Figure 7-4 Vulnerability assessment in the Halifax Peninsula, including (a) composite, (b) social (c) geophysical, and (d) mobility vulnerability

In addition, no vehicle ownership status of the household adds to evacuation risk of a zone. The distribution of female is around 44% - 64% for all the Peninsula TAZs. In the case of the highly vulnerable locations identified above, senior population distribution is observed to be greater than 39%. Few TAZs in the North-end area show a senior population distribution of 25%, while the rest of the TAZs have a distribution of less than 20%. The distribution of no vehicle households on several North-end and downtown core zones range between 33%-43%, while the distribution is typically 20-25% or less for the rest.

7.5.2 Relative Impacts of Variables on Vulnerability

To examine the relative impacts of a specific variable in determining vulnerability, this study conducts a sensitivity analysis for the variables of all three different vulnerabilities. For demonstration purpose, this study presents the impacts of variables of social vulnerability. To analyze the impacts of causal factors of social vulnerability, the node 'social vulnerability' is set as the target node in BN and the impacts of its causal factors are measured in term of conditional probability. Initially, Tornado diagrams are created to determine the impacts of variables on social vulnerability over each TAZ. Impact results of all individual TAZs are then aggregated to show how the impacts of different variables on social vulnerability differ spatially over the Halifax region. An example of a Tornado diagram for certain TAZs (e.g., GIS zone ID-17, 90, 95 and 100) is shown in **Figure 7-5**, where a variable with a wider bar reflects higher influence on vulnerability than variables with a smaller bar. The diagram shows the most sensitive parameters for a selected state of a target node (in this case, 'True state' for target node 'social vulnerability') sorted from the most to the least sensitive. We can select the number of parameters shown in **Figure 7-5** between top 10 and all. For the sensitivity analysis, the percentage of change in all parameters is considered as 10%. The horizontal axis shows the absolute changes in the posterior probability of social vulnerability for the state “True” when each of the parameters changes by the given percentage. The influence of the variables in relation to changing the vulnerability across TAZs can be derived from this Tornado diagram.

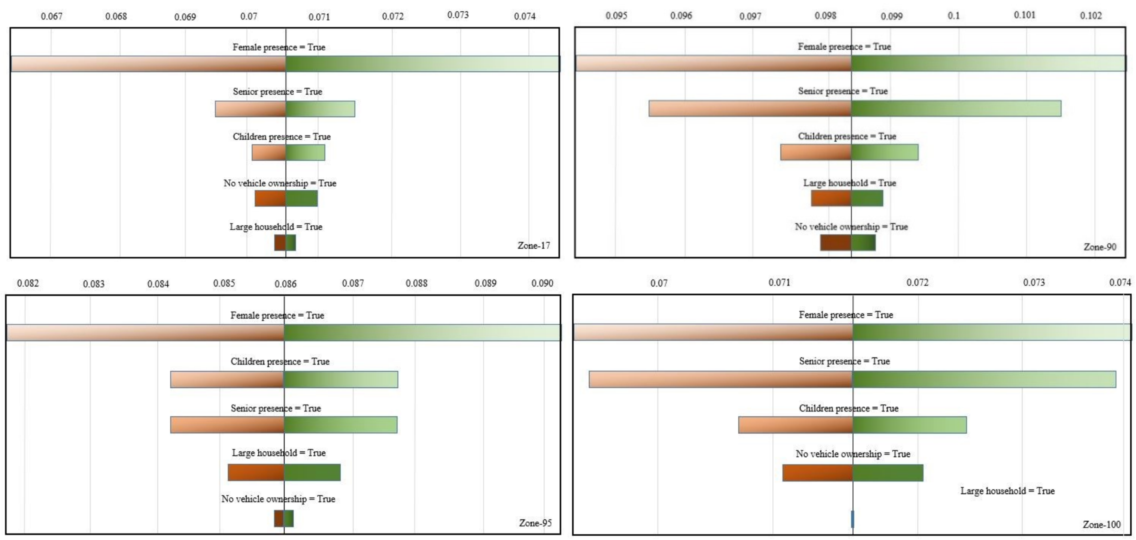

Figure 7-5 Tornado diagram for sensitivity analysis of vulnerability variables

Figure 7-6 shows how the degree of impacts of different variables (with a change of 10% in their current values) on the social vulnerability vary spatially over the Halifax region. Depending on the degree of the impacts of a variable corresponding to a TAZ (a spatial unit), the variable is assigned a rank in the parameter list of the Tornado diagram, which is used as the ‘spatial ranking’ in this study. A graduated color scale where the darkest represents a rank of 1, meaning the highest changes in social vulnerability due to changes in the variable. On the contrary, the lightest color represents a rank of 5 meaning the least changes caused by the changes in variable. The results show that the variable, ‘female presence’ is a key determinant of social vulnerability. This variable rank first to third in the list of the parameters of Tornado diagram in relation to the absolute changes in social vulnerability of different TAZs. However, for the majority of the TAZs, it ranks first. The variable ‘senior presence' is found to be the most impactful variable for several TAZs in the core, the North- and South-end of the peninsula. 'Children presence', and 'no vehicle ownership' contribute to social vulnerability sporadically. Variable 'large household' is found to be dominant in several downtown zones for the social vulnerability. The results suggest that 'presence of seniors and children', and 'large household' variables impact social vulnerability taking a rank in the parameter list from 1 to 5 while 'no vehicle ownership' holds its position from 1 to 4.

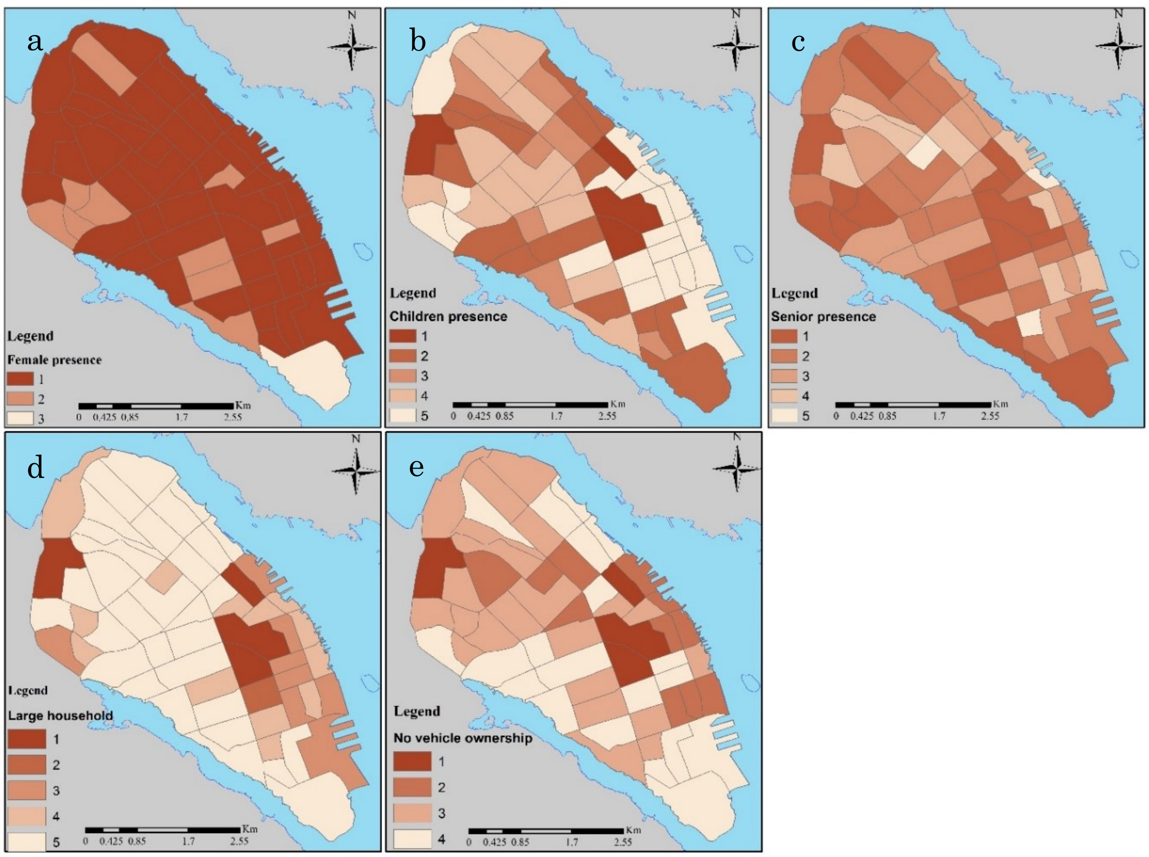

Figure 7-6 Sensitivity of social vulnerability variables over Halifax region where (a) female presence (b) children presence (c) senior presence (d) large household size (e) no vehicle ownership

This study also evaluates the relative impacts of the respective variables on geophysical and mobility vulnerability. 'Flood severity' and 'clearance time' are found to be the most impactful variables in case of geophysical and mobility vulnerability, respectively.

7.6 Conclusions

This study presented a framework to conduct vulnerability assessment in the context of a mass evacuation. The novelty of this study is that it combines an integrated urban systems model, a flood risk model and a traffic microsimulation model which will offer a unique opportunity to develop evacuation plans for future years. The proposed framework utilizes the information related to changes in population distribution, auto ownership, and traffic flows. One of the unique features of this study is that it utilized a BBN modelling approach for vulnerability assessment while addressing uncertainty and causal relationships in different elements of the vulnerability.

The proposed framework was empirically tested for a case study of Halifax, Canada. This study determined risky traffic analysis zones within the Halifax Peninsula in the light of information obtained from different models. Three vulnerabilities (social, geophysical, and mobility) were analyzed followed by developing a composite vulnerability within the BBN modelling framework. The AHP approach assigned different weighting factors to variables considered for BBN modelling. The probability estimation process has been enhanced by importing the importance of the risk and the risk factors into the BBN model. Composite vulnerability is found to be sporadically concentrated at the North- and South-End of the Peninsula, some parts of the downtown core, and the commercial area. A sensitivity analysis with a change of 10% in the values of each variable was conducted for an understanding of the impacts of variables on the respective vulnerability.

The developed integrated vulnerability assessment model will help to understand the spatial shifting of the vulnerable areas for different time horizon. The results will inform the prioritization of the areas based on a vulnerability index which can be the basis of zonal demarcation. It would be interesting to explore how zonal demarcation enriched with vulnerability information can assist a staged evacuation that would help minimize casualties, particularly focusing on the residents at the most perilous conditions. The remaining part of this thesis develops advanced models to devise countermeasures for improving the overall evacuation performances, particularly while ascertaining a vulnerability-based prioritization. The next two chapters capture vulnerability characteristics to prioritize zones for a staged evacuation and for allocating public transportation when considering an all mode evacuation scenario.

Chapter 8

Countermeasure: Vulnerability-based Staged Evacuation[5]

8.1 Introduction

This chapter develops a framework for mass evacuation modelling that considers staged evacuation during a hurricane or a flood for testing and evaluation. The strategic countermeasure, namely staged evacuation is important for a region like Halifax, which has a quite diverse population and a historical network that may suffer from time-varying different levels of severity during an evacuation. Staged evacuation involves sequencing of zones based on the priority needs for evacuation. It is a useful tool to control traffic inflows in the network, best utilizes the network capacity and thereby minimizes congestion level while moving the affected people to shelters or other identified safe zones efficiently. However, the process inherently induces ethical dilemmas and raises equity concerns. Different groups of people in a region suffer from natural disasters disproportionately due to their varying socio-economic characteristics and geographical locations. Therefore, pre-evacuation planning without the consideration of vulnerabilities may give a rise to societal and equity issues (Whitefield, 2006). For instance, low mobility

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[5] This chapter is partially derived from the following paper:

- Alam, M. J., and Habib, M. A. (2021). A Mass Evacuation Modelling Framework to Account for Vulnerabilities in Staged Evacuation. *Transportation Research Part A: Policy and Practice* (under review) people did not receive adequate attention during Hurricane Katrina in New Orleans. The group generally consists of seniors and persons of low-income, who do not own a car or have other options for evacuation. Several extreme events and large-scale evacuations have occurred in recent years and this trend highlights the vulnerability of cities to the impacts of the disasters. Simultaneously, in the past decade, hurricanes, wildfires, and tsunamis have broadened the understanding of evacuations and helped identify challenges, gaps, and opportunities for improvement. It has been observed that without any improvement strategy, alternatively countermeasure applied, conventional evacuation generally associates spontaneous behavior of evacuees leading to disorganization and consequently to a prolonged and/or incomplete evacuation. Therefore, a more efficient evacuation system is necessary, particularly for areas that contain vulnerable populations who are at high-risk and need a priority-based evacuation.

People are exposed to social and geophysical vulnerability when social vulnerability originates from their socio-economic status, life stage transition(s), and vehicle ownership. Geophysical vulnerability stems from their topographic locations. In addition, a high traffic demand and a long clearance time refer to the mobility vulnerability of an area. For example, the evacuation of a city's downtown area in the morning peak hours would be challenging and require a longer clearance time as the total population doubles at this period. Therefore, a systematic prioritization approach is of utmost importance to ensure that areas under perilous conditions have their priority needs considered when developing a staged evacuation plan. Generally, a staged evacuation is carried out by temporal and/or spatial shifting of evacuees' departures and requires prioritizing the area for evacuation that further creates an ethical dilemma and equity issues. For instance, a challenge of a staged evacuations which has not yet been adequately addressed in existing studies includes how to prioritize a low-income area over an affluent area.

Several staged evacuation studies (Chen and Zhan, 2008; Zhang et al., 2014) focused more on the traffic operation side of a staged evacuation process. These studies considered the distance of an area to the source of a threat for prioritization; however, other criteria, such as traffic congestion determines the amount of time a zone gets evacuated and is a critical dimension to assess the mobility vulnerability of the area. Hsu and Peeta (2014) considered natural hazards and network supply attributes to determine network vulnerability. However, there is limited research that holistically considered vulnerabilities in the prioritization process of a staged evacuation. Therefore, the objective of this study is to develop a framework of staged evacuation planning and modelling that assesses the priority needs of the vulnerable populations in relation to their geophysical, social, and mobility characteristics. Particularly, vulnerability assessment is useful for the evacuation of Halifax Peninsula as it has a quite diverse population group across neighborhoods within a small region. For example, SE is an affluent area while WE and NE represent the low-income and working population groups. The novelty of this research includes the development of a sequential modelling system that comprises of a fuzzy logic-based modelling approach to ascertain a vulnerability-based prioritization in assessing staged evacuation scenarios within a dynamic traffic microsimulation.

The identification and the prioritization of the areas containing vulnerable population for evacuation is dominated by human perception and is sometimes imprecise due to the use of non-numerical information regarding vulnerability. This warrants a probabilistic modelling or an approximate reasoning mechanism to handle the impacts of subjective information in human decision-making process. Fuzzy logic theory can efficiently deal with imprecision in the decision-making process based on qualitative information. This study employs a prioritization exercise and adopts a fuzzy logic approach to quantify the subjective prioritization by the expert. The exercise utilizes an integrated

Bayesian Belief Network-based vulnerability assessment model that provides vulnerability information considering socio-economic, geophysical and mobility factors. The evacuation scenario obtained from the proposed staged evacuation model is tested and evaluated within a traffic evacuation microsimulation model. The microsimulation model implements a dynamic traffic assignment process to simulate two evacuation scenarios for evaluation: (1) simultaneous evacuation (without any countermeasure/ coordination), and (2) staged evacuation. The scenarios are evaluated and compared through the analysis of traffic flow parameters, network performances and clearance times.

8.2 Literature Review

Evacuation modelling is an important element of emergency planning for coastal communities and regions that are prone to impacts of natural disasters. Existing literature demonstrates different processes of evacuation planning and modelling. Ukkusuri et al. (2017) and Gehlot et al. (2019) developed multi-agent microsimulation models called A-RESCUE (Agent-based Regional Evacuation Simulator with User Enriched Behavior) and a large version of A-RECUE called A-RECUE 2.0, respectively to capture detailed household behaviors when simultaneously handling a large evacuation traffic at network level following an adaptive routing strategy. Several approaches including econometric modelling (Sadri et al., 2015), cell-based network optimization modelling (Liu et al., 2006; Li and Han, 2015), traffic microsimulation and agent-based simulation modelling (Wang et al., 2016; Chen and Zhan, 2008) are used for evaluating evacuation decisions, e.g., route choices and testing contrasting evacuation plans. The simulation studies implemented either static or dynamic traffic assignment procedures in the network to predict traffic flows and network clearance time for a small- to large-scale evacuation event. In recent years, researchers have developed advanced models for capturing mobilization time and social network characteristics in accurately predicting evacuation demand (Sadri et al., 2013; Sadri et al., 2017). A recent study (Lindell et al., 2020) also focused on the household preparation time before the time household members decide to evacuate. Hence, delays in departure time were also estimated through this study. The study identified that storm characteristics, personal impacts and evacuation facilitators are key factors in the estimation of evacuation preparation time. Moreover, the Protective Action Decision Model (PADM) developed by Lindell and Perry (2012) signifies the importance of social warnings that may originate from multiple sources and be received by people directly or through intermediate media in building up people's perceptions of risks, and protective measures. Evacuation is convoluted by many factors and yields a sudden spike in traffic volume through a complex process. Abovementioned studies evolve to capture different levels of resolution within evacuation process and identify key challenges associated with the transportation network, which is not capable of accommodating the sudden influx in traffic demand during an evacuation (Lindell et al., 2018). Limiting capacity of the road network causes a mammoth of traffic congestion and thousands of people trapped on the road for an unknown amount of time. For example, the estimated auto-evacuation time was 36-48 hours during Hurricane Florence (Marshall, 2018) and in the evacuation for Hurricane Rita, people were stuck on the road for 10-12 hours (Blumenthal, 2005). Therefore, it warrants the development of evacuation traffic demand management strategies to regulate network traffic flows resulting from different levels of resolution of the evacuation dynamics and/or to increase the network capacity for an efficient evacuation.

Several studies devised different strategies including contraflow (Urbina, 2002) and staged evacuation (Chen and Zhan, 2008) to best use existing traffic infrastructure and their capacity in order to evacuate affected people in an efficient manner. Traffic operation-based strategies such as contraflow increases the network capacity by reversing one or more lanes outbound. On the other hand, staged evacuation considers sequencing of zones that are to be evacuated based on their priority needs. Simultaneous evacuation is adequately evaluated in the existing literature; however, limited studies focused on staged evacuation. There is a growing interest in studying nature, extents, procedures, and protocols in relation to staged evacuation. **Table 8-1** lists key studies and contributions in the field of staged evacuation. These studies encompass a wide variety of modelling methods ranging from network flow modelling to agent-based traffic simulation modelling and optimization techniques to devise and implement staged evacuation scenarios for prediction and evaluation. The staged evacuation scenarios considered in these studies are mainly focused on reducing network clearance time and improving evacuation and network performance. They used different criteria, including the distance of a zone from the source of a threat, population density, destination, and shelter requirements, and the first road segment's capacity to define vulnerable areas and prioritize them for a staged evacuation. Chen and Zhan (2008) found that the effectiveness of a staged evacuation strategy depends on the structure of the network and the population density. For example, a staged evacuation works better in a grid network with a high population density. However, this study created zonal divisions arbitrarily, and did not consider any of the socio-economic or geophysical vulnerabilities for prioritization. Malone et. al. (2001) utilized a cell-based automata model to test a staged evacuation scenario in different counties of South Carolina. This study links the performance of staged evacuation to only the severity and the path of a hurricane. Chen (2008) evaluated the staged evacuation of the Galveston area and observed a 1-hour improvement in clearance time. This study experimented with a hypothetical staged evacuation scenario but lacked a detailed method for prioritizing zones. Zhang et. al. (2014) examined traffic operation within a traffic microsimulation model for a staged evacuation scenario. They considered demand pattern and network structure to prioritize different regions for evacuation. Li et. al. (2012a) considered only geographical location to prioritize an area for evacuation. Abovementioned studies experimented several staged evacuation scenarios; however, there is a clear gap in developing prioritization processes that holistically evaluate vulnerabilities for testing as well as evaluating staged evacuation scenarios within a traffic microsimulation model. The existing studies did not outline a method for zonal prioritization based on vulnerabilities originating from geophysical, social and mobility challenges. Therefore, an integral planning and modelling approach is necessary to ascertain a vulnerability-based prioritization within staged evacuation model.

The proposed framework in this study fills the gap in literature by developing a fuzzy logic -based staged evacuation model that ascertains a vulnerability-based prioritization of zones at higher risks, informed by vulnerability indices when considering a staged evacuation. For a comprehensive vulnerability assessment, several vulnerability assessment models can be found in literature (Wood et al., 2010; Balica et al., 2012; Fuchs et al., 2011). A Bayesian Belief Network-based vulnerability assessment model (Alam and Habib, 2019a) provides vulnerability scores at the traffic analysis zonal level for this study. This study utilizes the output of the BBN model to design a prioritization exercise to receive expert opinion on how to prioritize traffic analysis zones given their vulnerabilities. Note that expert opinion is qualitative in nature. Fuzzy logic theory (Zadeh, 1965) is advantageous in creating approximate reasoning that can accommodate for imprecision in subjective judgment and quantifying the linguistic variables where conventional crisp choice models are not capable of handling the partial truth in decision making (Ridwan, 2004). Therefore, a fuzzy logic-based approach is adopted in this study to quantify the expert opinion in order to produce prioritization weights of traffic analysis zones.

One of the unique features of this study is that it develops a comprehensive staged evacuation modelling framework that addresses different aspects of vulnerabilities to prioritize areas for an evacuation and to predict the impacts of a staged evacuation on the traffic operation. The study employs a traffic microsimulation model to test and evaluate staged evacuation scenarios obtained from the proposed integral planning and modelling approach. The evaluation is carried out in terms of different traffic flow indicators including, traffic queues, clearance times, and intersection level of service (LOS).

Table 8-1 Key Studies and Contributions in the Field of Staged Evacuation

Authors	Methods	Evacuation type	Details/Contributions/Gaps	Findings
Chien and KoriKanthimath (2007)	Analytical modelling	Simultaneous and staged evacuation	Used speed-density relationship to model congestion, which does not guarantee capturing time-varying congestion spillback in the network. Only demand density is used as the criteria for staging, which may overlook the population group at higher risk.	Determined the minimum number of stages for a reduced evacuation time.
Li et al. (2012a)	Algorithm with three nested loops	Staged evacuation	Only geographic location of an area was used as the criteria for staging, which may overlook the residents that are socially vulnerable, and zones that require longer evacuation times.	Determined the earliest departure of each group and allowed each evacuee to choose shortest path avoiding congestion during evacuation.
Li and Claramunt (2018)	Analytical multi-objective problem	Staged evacuation	Scenarios in relation to using multiple exit allocation and nearest exit selection are evaluated. Focused on different evacuee types. However, the vulnerable population, e.g., seniors, were not prioritized.	Multi-exit allocation outperforms the nearest exit evacuation concept.
Zhang et al. (2014)	Traffic simulation modelling	Staged evacuation	Mainly focused on the traffic operation aspect. Demand pattern and network structure criteria were considered for staged evacuation. Effects of different levels of demand on the staged evacuation performances were discussed.	Phased evacuation improved overall efficiency over non-phased scenario. High demand in the network could alter the advantage of staged evacuation.
Liu et al. (2006)	Cell transmission - based network flow modelling	Staged evacuation	Small scale network experiment. No risk criteria were considered for staged evacuation optimization.	Optimized staged evacuation can mitigate congestion under various demand patterns.
Chiu et al. (2008)	Traffic simulation modelling	Simultaneous and staged evacuation	Staged evacuation in combination with contraflow is analyzed in this study.	Network performance improvement is not evident in case of staged evacuation without contraflow operation. However, phased evacuation in conjunction with contra flow operation significantly improved

Authors	Methods	Evacuation type	Details/Contributions/Gaps	Findings
				travel time with moderate improvement for inland zones.
Mitchell and Radwan (2006)	Traffic simulation modelling	Staged evacuation	Considered other factors in addition to geographical constraints; however, socio-economic characteristics and mobility issues are ignored to prioritize groups. Used Do-nothing assignment process which lacks actual representation of traffic congestion during an evacuation.	Six strategies were evaluated. Split scenario has slight clearance time reduction due to large departure time shift resulting in underutilized capacity. At low trip density, exits are underutilized and shifting departure time merely delays the clearance time.
Sbayti, and Mahmassani (2006)	A modified system-optimal dynamic traffic assignment; DYNASMART-P	Simultaneous and staged evacuation	A modified system-optimal dynamic traffic assignment is formulated to minimize total system trip time. Pre-evacuation traffic assignment path is assumed to be known, thereby static; however, impacted vehicles are provided with en-route information. Only trip time is considered for staging the demand.	Three staging policies representing three evacuation demand levels were evaluated. Overall, with the staged evacuation, total evacuation trip time is reduced by 31% and total network clearance time is reduced by 20%.
Bish et al. (2014)	Mixed-integer programming planning model	Staged evacuation	Performed staging at household level. This method may be useful in case of a large demand to utilize the network capacity adequately. Evacuee types are defined based on destination and shelter requirements. However, other criteria, e.g., household level vulnerability may also create different group types.	Explored demand management strategies and concluded that even with best managed supply strategies, there exists scenarios where the evacuation demand can cause congestion. Evacuee types based on destination and shelter requirements need to be included in evacuation planning.
Chen and Zhan (2008)	Agent-based modelling and simulation	Simultaneous and staged evacuation	Zonal division was done arbitrary. Network structures and demand density were highlighted in the study. Different network structures were evaluated in relation to staged evacuation performance. People from one zone was considered to leave at one time.	Performance of evacuation strategy depends on the structure of the network and population density. In a grid network with densely populated area, staged evacuation has the potential to reduce the clearance time. Simultaneous evacuation strategy is the best when traffic is in free flow

Authors	Methods	Evacuation type	Details/Contributions/Gaps	Findings
				mode. For the ring road, there is no benefit of using staged evacuation.
Chen (2008)	Traffic microsimulation modelling	Simultaneous and staged evacuation	Hypothetical staged evacuation scenarios were evaluated and compared to simultaneous evacuation. No detailed method for sub-dividing and/or prioritizing area presented.	There is an improvement of 1-hour reduced clearance time for Galveston area evacuation. Rapid response assumption is not supposed to lead to an effective evacuation; Ordering of zones influence overall staged evacuation performances.

8.3 Methodology

The sequential evacuation modelling system proposed in this study involves: (1) design of a prioritization exercise for experts utilizing a Bayesian Belief Network-based vulnerability assessment model, (2) adoption of a fuzzy logic approach to determine the prioritization weights of traffic analysis zones based on the experts' subjective prioritization in the exercise, and (3) utilizing the traffic evacuation microsimulation model for testing and evaluation of staged evacuation scenarios informed by the fuzzy logic-based staged evacuation model. The following sections describe each component sequentially.

8.3.1 Design of a Prioritization Exercise

This study designs a prioritization exercise, where experts evaluate the zonal vulnerability information and based on the perception of the zonal vulnerability, they prioritize zones for staged evacuation. To design the exercise, three vulnerabilities are considered: geophysical, social, and mobility vulnerability. In the case of zonal vulnerability, social vulnerability is estimated based on different factors, including percent of females, seniors, and children, income level, and vehicle ownership condition in a zone. Geophysical vulnerability is characterized by the distance of a zone from a flood source, and percentage of mobile homes. Mobility vulnerability is characterized by the zonal clearance time estimated from a traffic evacuation microsimulation model. A higher clearance time indicates a higher mobility vulnerability of a zone. As vulnerability is better described qualitatively, geophysical, social, and mobility vulnerability are categorized as Low, Medium, and High. A hypothetical pair of zones with similar vulnerability information is presented to the experts for prioritization. Each pair of zones is represented by two boxes on a single card as shown in **Figure 8-1**.

Card 1: Tick the box for the zone you choose to prioritize for evacuation

☐ Zone A

☐ Zone B

Zone A

Zonal Social Vulnerability: **LOW**

Zone to Shelter Clearance Time: **12.5**

Zone B

Zonal Social Vulnerability: **MEDIUM**

Zone to Shelter Clearance Time: **5.0 Hours**

Figure 8-1 A sample card from the prioritization exercise

8.3.1.1 Prioritization Exercise through a Stakeholder Workshop

This study is informed from a stakeholder workshop titled “Improving Emergency Response to Extreme Coastal Weather”. It was organized by the MacEachen Institute for Public Policy and Governance and Dalhousie Transportation Collaboratory (DalTRAC) at Dalhousie University in Halifax, Canada. The workshop had 46 participants from many sectors including government and non-government organizations as well as federal, provincial, and municipal agencies. A composition statistic of the participants is presented below in **Figure 8-2**.

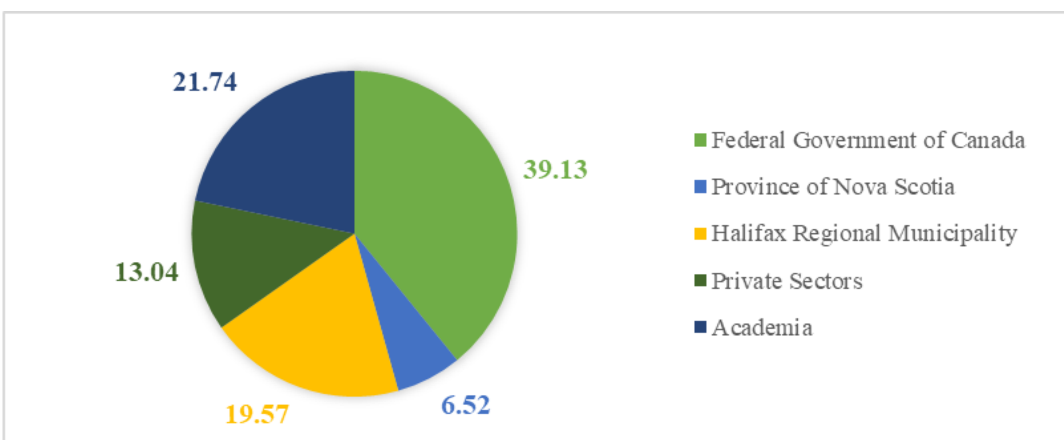

Figure 8-2 Stakeholder categories by percentage

The participants work with Emergency Management Organizations (EMOs), NS Environment, Public Safety Canada, Public Health Agency Canada, MSC-Atlantic, Canadian Armed Force, Care Facilities, Institute of Catastrophic Loss Reduction, where their responsibilities involve a significant amount of emergency planning and management activities, warning and preparedness during emergency conditions. They have significant experience in hurricane forecasting, evacuation drill and developing evacuation plans at community, national and international levels.

The purpose of the workshop was to receive expert opinion on how to conduct a mass evacuation process. The workshop included focus discussions and participatory activities that inquired, for instance, "what are the major considerations in selecting areas to evacuate?" and "how would stakeholders prioritize areas for a mass evacuation?". The prioritization exercise was designed as a part of this workshop and conducted in order to better understand the actual prioritization processes. The qualitative response from the experts was recorded, aggregated, and quantified by using a fuzzy logic approach to estimate the prioritization weight for each traffic analysis zone in Halifax.

8.3.2 Fuzzy Logic - based Approach for Prioritization Weights

The vulnerabilities of traffic analysis zones and the prioritization by the experts obtained from the workshop are subjective in nature that involves imprecise and non-numerical information. Therefore, this study adopts a fuzzy logic approach to analyze the qualitative response by the experts when prioritizing zones for evacuation. The proposed fuzzy logic framework provides a mathematical mean to quantify the qualitative judgments and facilitate ranking of zones for evacuation.

The subjective prioritization information provided by the experts is incorporated into a fuzzy logic framework to determine a prioritization weight for each traffic analysis zone (TAZ). Fuzzy sets are developed to define the geophysical, social, and mobility vulnerability by the fuzzy linguistic variables. A fuzzy set is a collection of elements in a universe of information and defined by a membership function. The membership function assigns membership values to the elements, which represent the membership or grade of a given element to the fuzzy set (Hawas, 2011). A fuzzy set can take any value within the closed interval [0, 1]. The larger value (i.e., closer to 1) represents the higher degree of membership. The value in between 0 and 1 expresses a partial membership of an element to a fuzzy set. The shape of the membership functions includes triangular, trapezoidal, gaussian, and sigmoidal. The simplest fuzzy membership function uses a linear relationship to define the membership grade of any element in the input space (Ali and Sumai, 2015). Triangular and trapezoidal are found to be the most efficient based on empirical evidence (Gholamy et al., 2020). Therefore, this study adopts a triangular shape for the analysis. Assume, μ represents the membership values of a set of triangular membership functions and x is the element of the function that takes the crisp values. The triangular membership functions can be described as follows:

$$\mu(x) = \left\{ \begin{array}{ll} \frac{x-r}{s-r}, & \mathrm{r} \leq \mathrm{x} \leq s \\ \frac{t-x}{t-s}, & \mathrm{s} \leq \mathrm{x} \leq t \\ 0, & \text{otherwise} \end{array} \right\} \tag{1}$$

A three-stage fuzzy logic approach is adopted in this study, which includes (1) fuzzification, (2) fuzzy inference, and (3) de-fuzzification. In the fuzzification stage, the membership function for each fuzzy set is determined. Fuzzy inference is the process used to populate the inputs and generate outputs based on certain fuzzy rules. Defuzzification is an important and a final phase which involves translating the fuzzy inference output to a crisp value.

8.3.2.1 Fuzzification: Linguistic Variables for Vulnerabilities and Prioritization

This study develops fuzzy membership functions for three input variables: (1) geophysical vulnerability, (2) social vulnerability, and (3) mobility vulnerability i.e., clearance time. The element (x), alternatively score or index of input variables 'geophysical vulnerability' and 'social vulnerability' are obtained from a Bayesian Belief Network-based vulnerability assessment model. The input variables are classified based on the distribution of all zonal vulnerability scores. In case of social and geophysical vulnerability scores, most of the data points are below or equal to a score 0.1 (80%), and there rarely exists data points beyond 0.3. Thus, these two variables are classified into three groups and defined by its numerical element (x): Low (0.0-0.1), Medium (0.1-0.3), and High (>0.3). In the case of the variable 'clearance time' for mobility vulnerability, a traffic evacuation microsimulation model is used to estimate the zonal clearance time and define the linguistic term of this variable accordingly. The simulation model estimates that the clearance times for most of the zones are less than or equal to 10 hours, which comprises of around 93% of TAZs. Few TAZs require clearance time greater than 15 hours and the rest of the TAZs are evacuated in 10-15 hours. Therefore, mobility vulnerability is grouped into three classes: Low (0-10), Medium (10-15), and High (>15). To define the linguistic terms of the output variable 'prioritization weight', this study utilizes the workshop results. The percent experts prioritize zones with different vulnerability conditions are estimated. The study created four linguistic variables for the "Prioritization weight". Based on the response from the workshop, it has been found that zones with any of six different vulnerability conditions (e.g., a condition refers to low social and medium mobility vulnerability) are prioritized by 10% or less participants, which gives the first linguistic variable classified as 0-10%. There are zones with another three different vulnerability conditions which are prioritized by 10% to 22% of experts resulting in the next linguistic variable defined by 10% - 30%. Similarly, the other two linguistic variables are found to have weighting classes between 30 and 40% and > 40% respectively. As prioritization is a ranked variable and based on the order of weighting classes, the four linguistic variables for prioritization are termed as Low (0 - 0.1), Medium (0.1 – 0.3), High (0.3 – 0.4), and Very High (> 0.4). **Table 8-2** presents linguistic terms and numerical elements for all the input and output variables.

Table 8-2 Elements of Linguistic Variables for Each Attribute

Linguistic variables	Geophysical vulnerability score	Social vulnerability score	Mobility vulnerability (clearance time, hr.)	Prioritization weights
Low	0-0.1	0-0.1	0-10	0-0.1
Medium	0.1-0.3	0.1-0.3	10-15	0.1-0.3
High	> 0.3	> 0.3	> 15	0.3-0.4
Very high	-	-	-	> 0.4

The information from **Table 8-2** is then used to develop triangular fuzzy sets for all attributes considered in this study. Fuzzy sets for input and output variables are shown in **Figure 8-3**. Next, linguistic variables obtained from the fuzzification stage are used for making fuzzy inferences.

8.3.2.2 Fuzzy Inference: Inferring Relations between Vulnerabilities and Prioritization

This study uses a set of "If-Then" logic statements in the fuzzy inference phase. For example, the following logic is used for inferring the relationship between a zone's vulnerability, and the prioritization of that zone.

*"**IF** Social vulnerability of a zone is [Low], and Clearance time is [Medium], **THEN** the prioritization of the zone is [Low]"*

Based on the percent respondents that prioritize a zone given its vulnerabilities in the workshop, a set of fuzzy rules similar to above are created. Fuzzy rules are utilized to identify the fuzzified category of prioritization and a max.-min. composition method is used to calculate the corresponding membership values in this stage. The output from fuzzy inference further informs defuzzification process in the next phase.

8.3.2.3 Defuzzification: Prioritization Weights for Traffic Analysis Zones

To convert the fuzzy inference outputs to a crisp value, this study applies the center of gravity technique (Kikuchi and Miljkovic, 2001) in the defuzzification stage. The expression used to derive the crisp output value $\psi*$ is shown below:

$$\psi* = \frac{\int \mu(\psi) y \, \mathrm{d}\psi}{\int \mu(\psi) \, \mathrm{d}\psi} \tag{2}$$

Where, $\psi*$ is the crisp value, which continuously changes with the change in input values.

8.4 Application of the Proposed Framework for Prioritization

The computation at three fuzzy stages requires the following operations: (1) fuzzification that generates linguistic variables for the input and output variables, (2) fuzzy inference that outputs linguistic variables and corresponding membership values based on certain fuzzy rules and (3) defuzzification that computes crisp values for prioritization weights. As shown earlier in **Table 8-2**, three linguistic variables are defined for each of three input sets and four linguistic variables for an output set at the fuzzification stage. Using the definition of the linguistic variables presented in **Table 8-2**, the following input-output fuzzy sets are developed in **Figure 8-3**.

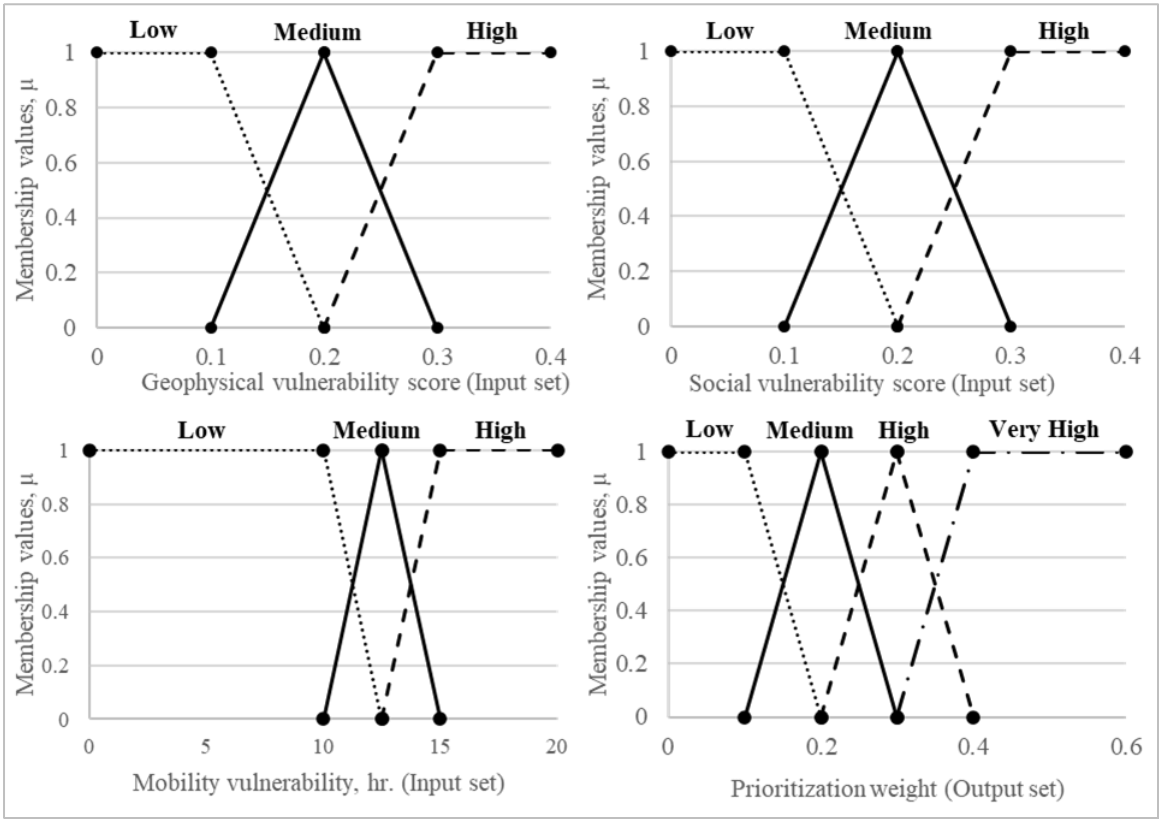

Figure 8-3 Fuzzy sets for input and output variables

Based on the outcomes of the prioritization exercise by the experts, this study develops thirteen fuzzy rules for the fuzzy inference stage. In this method, the input value of each variable defines one or two fuzzified category e.g., Low, and/or Medium and corresponding membership values are obtained using the membership functions shown in **Figure 8-3**. For example, a value in between 0.1 and 0.2 for social vulnerability indicates both Low and Medium membership of the variable to the fuzzy sets. All the probable combinations of fuzzified categories are developed and matched with the applicable fuzzy rule. Suppose variable 1 indicates both the Low and Medium fuzzified categories in relation to its numerical score, and variable 2 belongs to a single category, for example, High. Then two possible combinations include (1) input variable 1 is Low, and input variable 2 is High, and (2) input variable 1 is Medium, and input variable 2 is High. The combinations are then matched with applicable fuzzy rules to determine the fuzzified category for prioritization and corresponding membership values. The output fuzzified category and membership value obtained are then used in max.-min. composition process demonstrated in **Table** 8-3. The final fuzzy inference output i.e., membership values are utilized in the next phase 'Defuzzificaion' to obtain the crisp value representing prioritization weight of the intended zone. A sample calculation is shown in **Table** 8-3 for the demonstration of fuzzification, and the max-min composition method used in fuzzy inference stage. Furthermore, **Figure 8-4** shows the defuzzification process used to convert the fuzzy inference output to a crisp value.

Table 8-3 Demonstration of Fuzzification, and Fuzzy Inference

Zone: 54				
Fuzzification output				
Input variables	**Input values**	**Fuzzified category from Figure 3**		**Membership grade from Figure 3**
Social vulnerability	0.22	Medium		0.80
		High		0.20
Clearance Time, hr.	5.58	Low		1.0
Fuzzy inference				
Applicable Rule #	**Input variables**			**Max-min composition output**
	Social vulnerability	**Clearance time**	**Prioritization from exercise**	
Rule: 3	Medium (0.80)	Low (1.0)	Medium	Min (0.80, 1.0) = 0.80
Rule: 6	High (0.20)	Low (1.0)	High	Min (0.20, 1.0) = 0.20
				Prioritization Medium: Max (0.80) = 0.80 Prioritization High: Max (0.20) = 0.20

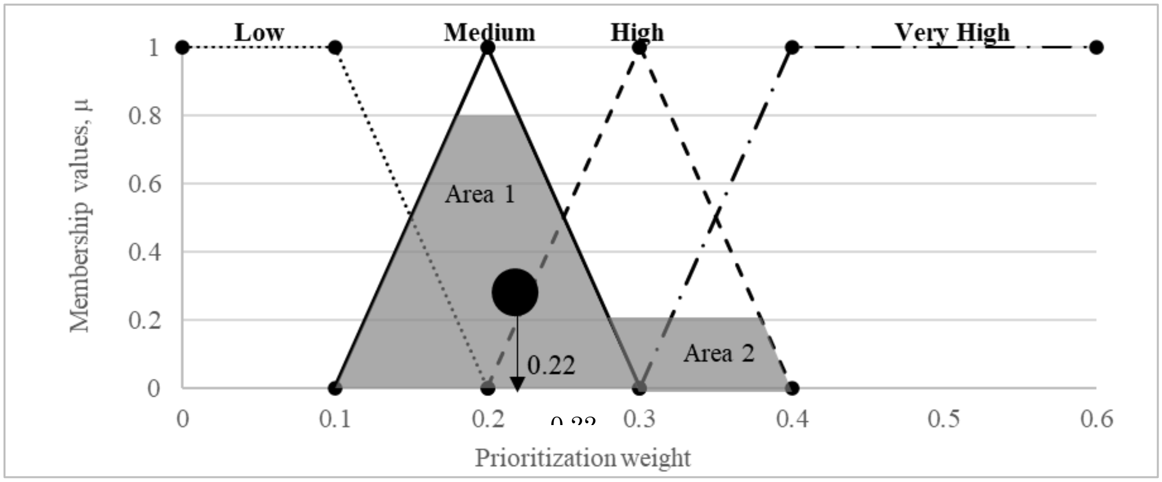

Figure 8-4 Defuzzification for prioritization weights of traffic analysis zones

The crisp value of 0.22 obtained through defuzzification represents the centroid of the shaded region in **Figure 8-4** and is estimated using the center of gravity rule. The Area 1 under Medium membership function with respect to 0.80 and the Area 2 under the High membership function with respect to 0.20 comprise the shaded region together. Both values of 0.8 and 0.2 are obtained from the fuzzy inference output for Medium and High prioritization respectively as shown in **Table** 8-3. This study identifies four planning districts comprised of traffic analysis zones within the Halifax Peninsula for the purpose of a staged evacuation. The prioritization weights of the zones are utilized to develop the prioritization ranking of these districts for evacuation. The developed traffic microsimulation model accounts for the ranks of the districts for evacuation when implementing the dynamic traffic assignment process.

8.5 Traffic Microsimulation Modelling of Staged Evacuation

The traffic evacuation microsimulation model developed in earlier chapters is utilized to test and evaluate staged evacuation scenarios in this chapter. In total, 65,000 vehicles are simulated for a simultaneous evacuation scenario considering two shelters and one external safe zone, representing a relative, and/or friends' places. This scenario represents an evacuation scenario when no staged evacuation strategy is applied. To conduct a staged evacuation, a sequential staging of traffic demand is performed on an incremental basis. To sequentially assign evacuation traffic in the network following the prioritization ranking, a certain percentage of evacuation completion of the preceding zone needs to be estimated to determine the starting time of the succeeding zone. This study uses the same percentage of evacuation completion of preceding zones until the last zone participates in the evacuation. An iterative approach is adopted to identify the optimum evacuation completion percentage to obtain the starting times of the evacuation of different districts. Starting with a 25% completion, and with a 5% increment, different completion percentages ranging in between 25 to 50% are evaluated in terms of minimum total evacuation time required. The simulation suggests that using the evacuation starting times for four planning districts corresponding to the completion percentage of 25 to 35% yields the minimum total evacuation time. In the case of starting times in relation to a completion percentage above 50%, the total evacuation time is found higher compared to the evacuation without staging. Four origin-destination matrices are developed for the four planning districts and are assigned in the traffic evacuation microsimulation model using the final evacuation starting times.

8.6 Results and Discussions

8.6.1 Prioritization Weights of TAZs for Staged Evacuation

For the analytical and staged evacuation process, all TAZs are grouped into four planning districts such as 'Downtown (DT)', 'West-End (WE)', 'North-End (NE)', and 'South-End (SE)' (**Figure 8-5**). **Table 8-4** presents the proportion of traffic analysis zones within all planning districts of the Halifax Peninsula under different categories of prioritization weights. The results reveal that the planning districts 'DT' and 'WE' contain traffic analysis zones with higher priority needs during the evacuation.

Table 8-4 Prioritization Weights of Traffic Analysis Zones under Four Planning Districts

Prioritization weights	Proportion of traffic analysis zones (%)			
	DT	WE	NE	SE
<0.1	50	75	81	82.3
0.1-0.2	37.5	8.3	19	17.7
>0.2	12.5	16	-	-

Poverty and affluence co-exist in Halifax neighborhoods (Prouse et al., 2015). It has been found that planning district 'SE' is the area of affluence and 'NE' is known as a working-class and low-income district with a negative reputation (Silver, 2019). Although, average income of the 'NE' district increased in 2010, it remained below the average stated in the Census of the Metropolitan Area. In the case of 'WE', which is an inner suburban area of Halifax, the average income has decreased over the last 30 years. 'DT' is a small district when compared to the others and has a highly dense population, predominantly students or young professionals, who share accommodations and use transit for travel. The percent of large and non-vehicular households is higher in 'DT' compared to other districts. In this district, 6.4% of the residents use transit for their travel. From a geophysical risk perspective, peripheral and several other zones in 'NE' and 'DT' are prone to inundation during a flood. Based on the prioritization results, the maximum weight assigned to different planning districts for social vulnerability are 0.13, 0.15, 0.24, and 0.11 for DT, NE, WE, and SE, respectively. From the mobility vulnerability perspective, DT is prioritized with a maximum weight of 0.3. Considering three different vulnerabilities, DT is the most vulnerable district, and it needs to be addressed accordingly within the staged evacuation plan. Similarly, prioritization weights for other districts are analyzed to inform staged evacuation scenario building process within the traffic microsimulation model. The prioritization results reveal that social and mobility vulnerability have a large contribution to the prioritization process for staged evacuation. Without considering them and solely relying on the geophysical dimension, staged evacuation may not entirely encompass the areas or people at high risks that genuinely need to be incorporated into the special evacuation plans. The results also reveal that the prioritization of the planning districts is dominated by the mobility aspects indicating that special evacuation plans, or countermeasures need to focus on the reduction of evacuation times and network congestions in the network. For example, bus evacuation accommodating transit-dependent as well as a portion of auto-user could reduce the traffic in the network which will further reduce the evacuation time.

8.6.2 Staged Evacuation Scenarios

Based on the prioritization weights of traffic analysis zones obtained from the staged evacuation model, the prioritization results for all planning districts reveal that 'DT' ranks first and 'WE' ranks second for prioritization in relation to their social and mobility vulnerability. On the other hand, 'NE' ranks first, and 'DT' ranks second for prioritization when geophysical vulnerability is considered. However, this study adopts a holistic approach of combining all three types of vulnerabilities to identify prioritization ranking. Based on the scores of planning districts considered, the order of the planning districts for staged evacuation within the traffic microsimulation model is obtained as follows: DT>WE>NE>SE. Based on starting times obtained from the traffic simulation model, the demand assignment starts at 10:00 am for 'DT' followed by the assignment for 'WE' at 4.5 hours (2:30 pm), for 'NE' at 6 hours (4:00 pm), and for 'SE' at 6.5 hours (4:30 pm).

8.6.3 Overall Network Performance for Staged Evacuation

This study examines overall network performance for a staged evacuation in Halifax. **Figure 8-5** illustrates traffic flows across major arterial streets, highways, and bridges in the Halifax transport network. Downtown roads are highly congested due to a high population density and the presence of saturated intersections. The intersection 'Lower at Duke Street' in this planning district exhibits a level of service 'F' for most of the evacuation time (see **Figure 8-6**). The overall network performance results in **Table 8-5** suggest that the average delays and the total distance travelled are higher between approximately the 4th and 10th evacuation hour. This is the time when traffic from all planning districts is admitted into the network. Therefore, the number of traffic and traffic movements peak at this period.

This study also examines traffic congestion in terms of queue time experienced by traffic from different TAZs presented in **Figure 8-7**. It shows the box plot of the queue time for TAZs in four planning districts. TAZs in 'WE' experience a uniform and consistent congestion as this district is located close to three exits. For certain zones e.g., z14 and z25 of 'NE' district in **Figure 8-7** , the box plot shows relatively a taller upper whisker indicating a greater chance for these zones to anticipate higher queue times.

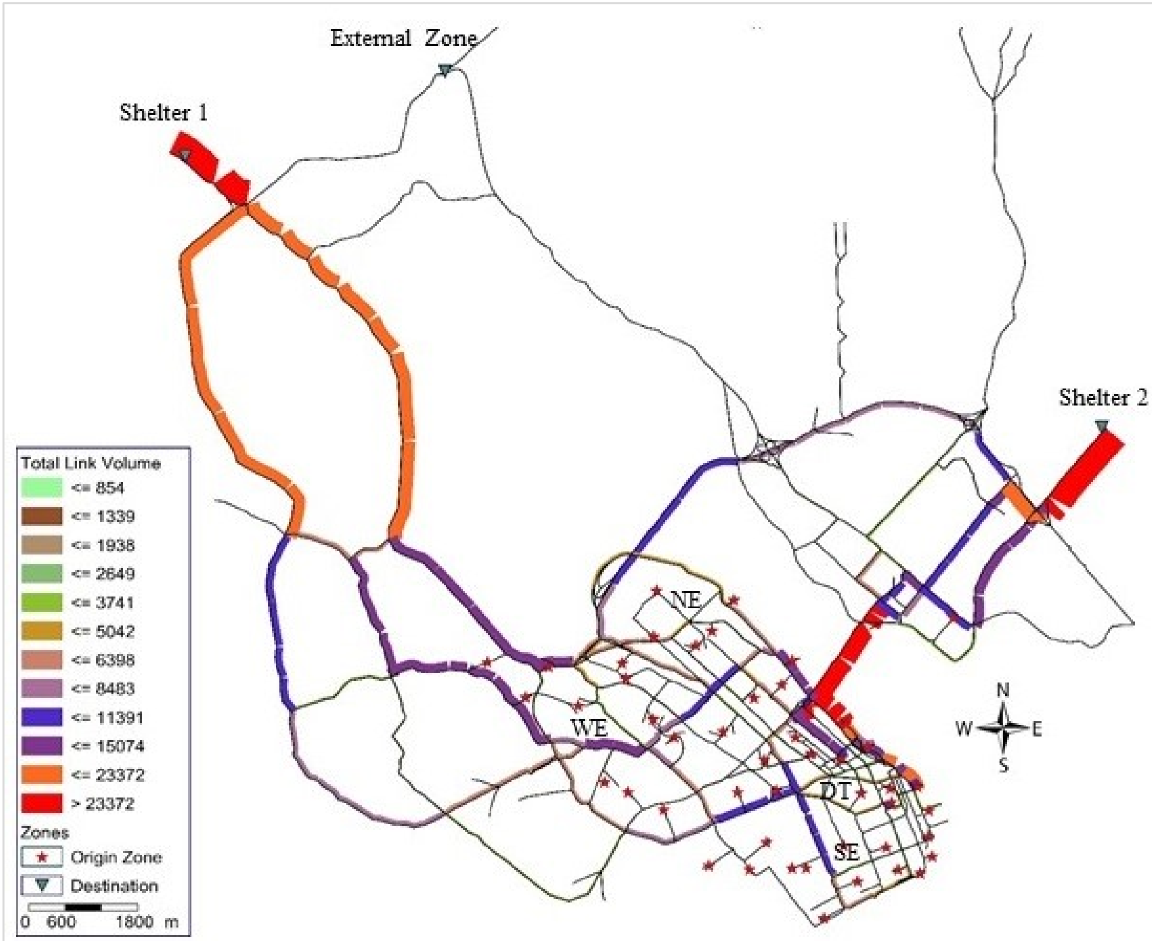

Figure 8-5 Origins, shelter locations, and traffic flow visualization in the network

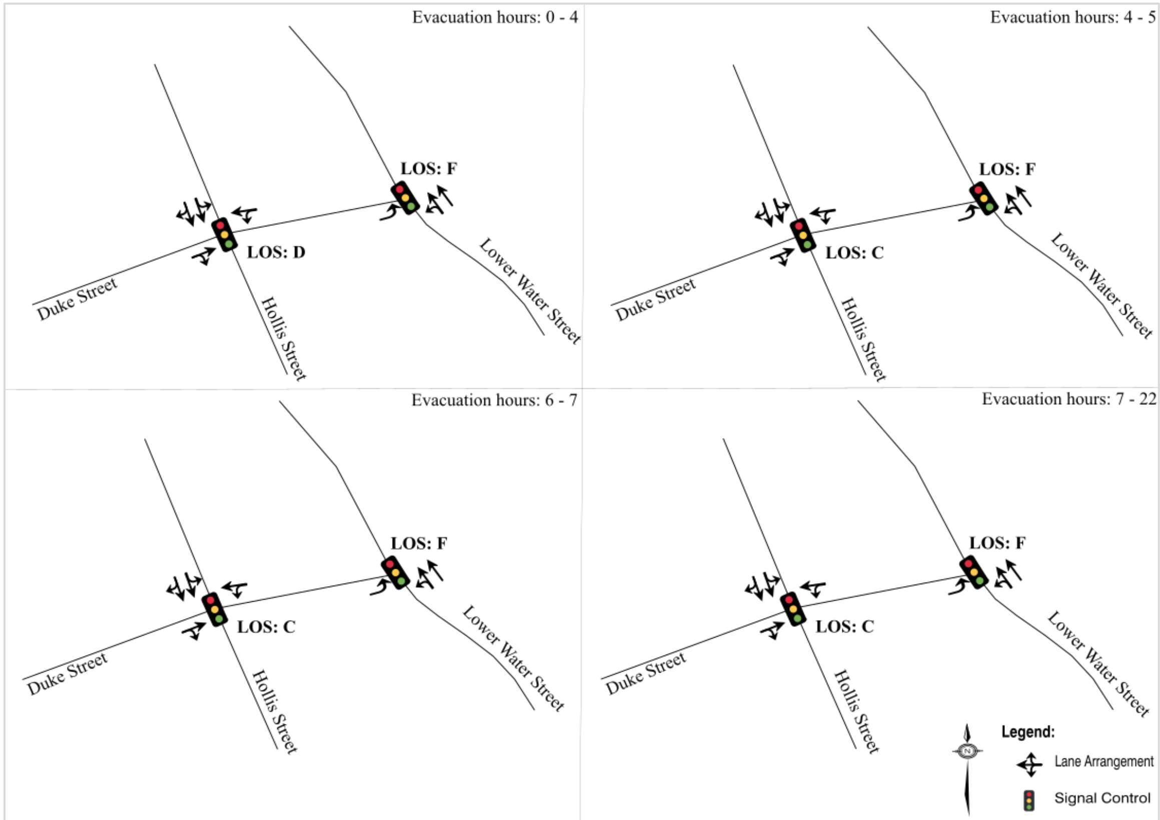

Figure 8-6 Level of Service (LOS) at intersections 'Lower Water St at Duke St' and 'Hollis St at Duke St' for a staged evacuation of the Halifax Peninsula

The reason is that evacuees from these zones travel across the city to arrive at a distant shelter. **Figure 8-7** also shows that Downtown traffic congestion is consistent as the box width is minimal.

Table 8-5 Overall Network Performance for a Staged Evacuation

Evacuation hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Acting vehicle# in network	2848	1604	1034	1100	5151	1656	8322	4503	2783	1455	1265	1297	1303	1313	1255	874	602	618	601	317	5
Total arrival at shelters	2852	3381	1869	2297	2872	4995	5063	5312	4729	4556	3272	2969	3115	3158	3248	3020	2365	1648	1703	1421	744
Avg. Travel Time (min)	45.5	37.9	36.1	32.7	48.6	40.4	72.7	70.1	44.3	27.7	23.8	26.4	25.1	25.0	24.1	21.6	20.5	21.5	21.1	19.7	18.5
Avg. Delay (min)	8.6	14.1	12.1	6.9	6.4	17.8	17.4	27.1	16.1	8.8	3.9	4.2	3.8	3.7	3.6	3.8	3.1	3.1	3.1	3.3	3.6
Avg. Speed (km/hr.)	27.3	19.8	21.0	30.1	27.6	18.1	16.2	12.5	18.6	25.5	33.9	33.7	34.3	34.7	34.7	34.0	35.6	35.1	35.4	35.0	35.4
Total Distance Travelled (km)	59.1	42.3	23.6	37.7	64.3	61.1	99.2	77.6	65.0	53.5	43.9	44.0	44.6	45.6	45.3	37.1	28.8	20.8	21.2	16.4	8.1
Avg. Stop#	29.2	43.6	34.6	19.8	20.7	61.9	43.2	70.8	52.0	30.4	12.8	13.9	12.0	11.8	11.4	12.8	10.5	10.7	10.2	11.8	14.6

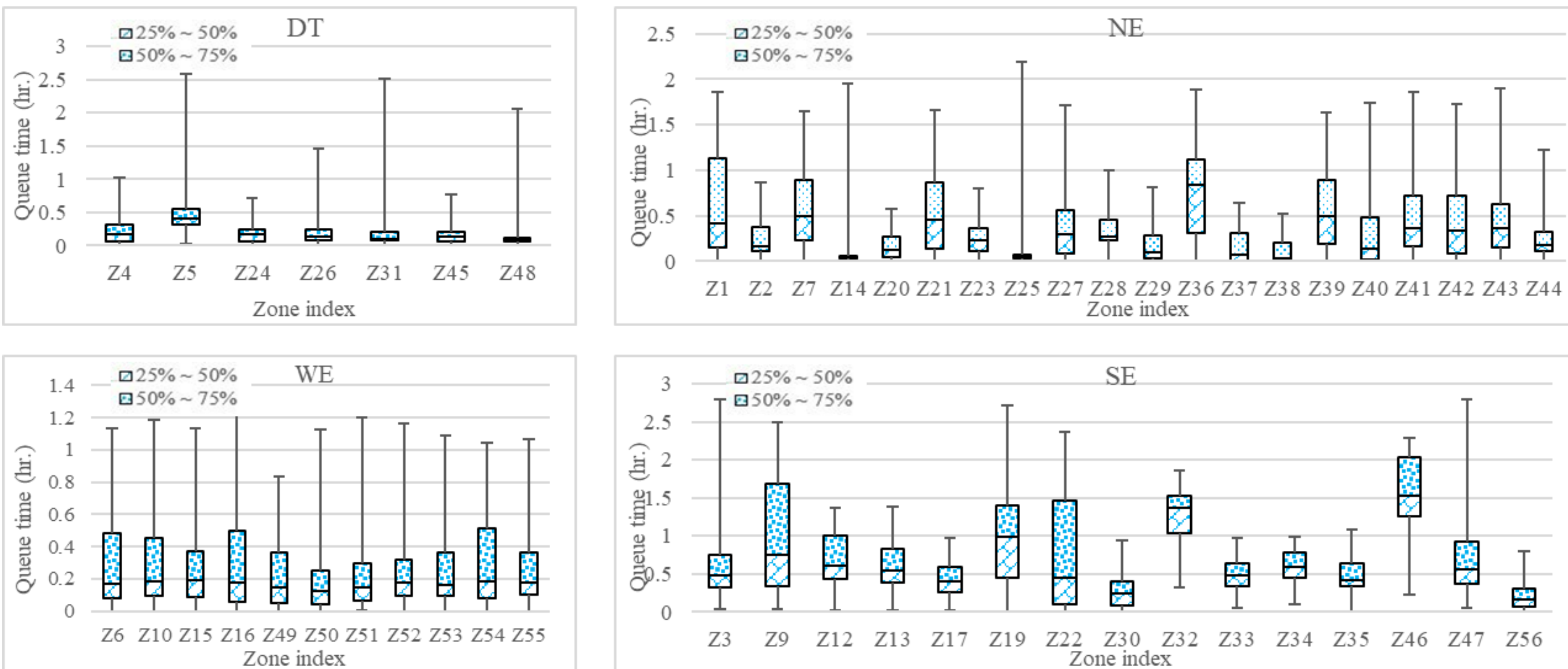

Figure 8-7 Queue time experienced by traffic analysis zones within four planning district

8.6.4 A Comparison of Simultaneous and Staged Evacuation

8.6.4.1 Traffic Flow Attribute Analysis

Table 8-6 shows the comparison of different network performance attributes for two alternative evacuation scenarios: simultaneous and staged evacuation. In the case of a staged evacuation process, though Downtown congestion did not improve significantly, most of the attribute values indicate an improvement for overall network performance. Travel time requirements, average delays, and the total distance travelled are lower in magnitude compared to those of a simultaneous evacuation. In comparison to a simultaneous evacuation, average travel time decreases by 39.5% in staged evacuation scenario during the most congested period. In addition, the average speed improves in the staged evacuation scenarios.

8.6.4.2 Clearance Time Analysis

This study examines evacuation performance across planning districts and traffic analysis zonal levels. **Table 8-7** presents the total clearance time for each planning district in both simultaneous and staged evacuation scenarios. Furthermore, **Figure B – 6** in **Appendix B** presents clearance time for each TAZ within the four-planning districts for staged evacuation. The results suggest that the clearance time improvement resulting from a staged evacuation is quite significant compared to an evacuation without any countermeasure, a decrease from 24.31% to 70.37% in clearance time for 'WE', 'NE' and 'SE'. The clearance time improvement for 'DT' district is relatively less due to the presence of several densely populated traffic analysis zones and saturated intersections as consistent with the findings of Zhang et al. (2014). To investigate the improvement at traffic analysis zonal level, this study estimates zonal clearance time as shown in **Table 8-7**. The results reveal that 75% of the traffic analysis zones in planning district 'WE' and 'NE' anticipate a maximum decrease of 4.8 and 4.3 hours respectively in clearance time. 'SE', the area of affluence, also anticipates a maximum clearance time reduction of 4.4 hours for 75% of its traffic analysis zones. An interesting finding is that although 'SE' ranks last in the prioritization process, due to the inherent transportation system efficiency, well connected and spacious roads, and less traffic volume benefit this district during an evacuation. However, accounting for vulnerabilities improves the staged evacuation process by reducing disparity among areas when prioritizing them in an equitable manner. On the other hand, the results for the DT evacuation indicate that a staged evacuation is not always an effective strategy that works for extreme events resulting in a mass evacuation. We need additional countermeasures combined with it. For example, DT's clearance time decreases by 2.8 hours for 50% of the zones, which is relatively lower than the other districts (**Table 8-7**). There are also zones within the DT district that show a slight decrease (0.3 hours) in clearance time. This is likely a result of the limited design capacity of existing infrastructure and a high population density. As vulnerability-based staged evacuation in this study did not significantly improve operational efficiency for certain zones, there needs to be infrastructure improvement-based countermeasures implemented at different locations, particularly around vulnerable areas.

In addition, a finer level analysis of microsimulation results is conducted for further understanding of the staged evacuation performance within the planning districts. **Table 8-7** shows the percent to which individuals in each planning district are impacted due to a staged evacuation. The results reveal that though the clearance time for planning districts improves, there are individuals who are disadvantaged in a staged evacuation. The reason is that shifting of the departure times may cause an individual to travel in a congested traffic regime compared to a previous less congested traffic regime in conventional evacuation scenario.

Table 8-6 Comparative Network Performance for Simultaneous and Staged Evacuation

	Evacuation hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Simultaneous evacuation	Avg. Travel Time (min)	54.3	71.7	80.1	78.5	61.1	52.6	35.6	30.5	27.0	26.0	25.2	28.7	27.4	27.0	22.4	23.7	23.7	21.9	22.7	23.9	24.1
	Avg. Delay (min)	8.6	17.9	23.5	24.8	24.6	19.5	12.9	8.1	5.1	5.3	5.6	6.6	6.3	6.5	3.5	3.8	3.9	3.0	3.3	3.4	3.3
	Avg. Speed (km/hr.)	26.9	17.7	13.4	12.3	12.7	15.7	20.7	26.5	31.9	31.1	30.9	28.8	29.2	29.7	34.5	34.1	34.0	36.6	35.3	35.4	35.6
	Total Distance Travelled (km)	89.0	117.9	110.9	103.4	78.5	60.0	52.0	44.3	50.4	44.4	38.2	28.5	29.4	27.5	20.1	19.0	18.6	22.3	12.1	12.4	12.6
	Avg. Stop#	46.7	71.9	83.9	72.3	70.7	66.0	53.9	39.4	32.1	45.0	48.3	60.4	57.2	58.2	29.4	32.4	32.5	20.7	29.3	26.5	27.1
Staged Evacuation	Avg. Travel Time (min)	45.5	37.9	36.1	32.7	48.6	40.4	72.7	70.1	44.3	27.7	23.8	26.4	25.1	25.0	24.1	21.6	20.5	21.5	21.1	19.7	18.5
	Avg. Delay (min)	8.6	14.1	12.1	6.9	6.4	17.8	17.4	27.1	16.1	8.8	3.9	4.2	3.8	3.7	3.6	3.8	3.1	3.1	3.1	3.3	3.6
	Avg. Speed (km/hr.)	27.3	19.8	21.0	30.1	27.6	18.1	16.2	12.5	18.6	25.5	33.9	33.7	34.3	34.7	34.7	34.0	35.6	35.1	35.4	35.0	35.4
	Total Distance Travelled (km)	59.1	42.3	23.6	37.7	64.3	61.1	99.2	77.6	65.0	53.5	43.9	44.0	44.6	45.6	45.3	37.1	28.8	20.8	21.2	16.4	8.1
	Avg. Stop#	29.2	43.6	34.6	19.8	20.7	61.9	43.2	70.8	52.0	30.4	12.8	13.9	12.0	11.8	11.4	12.8	10.5	10.7	10.2	11.8	14.6

Table 8-7 Comparison of Clearance Times for Simultaneous and Staged Evacuation

Planning districts	Fuzzy logic-based prioritization	Total network clearance time			Changes in zonal clearance time			Percent individual impacted	
	Prioritization rank	Simultaneous evacuation (hr.)	Staged evacuation (hr.)	Percent reduction	25% of zones (hr.)	50% of zones (hr.)	75% of zones (hr.)	Travel time improvement (%)	Travel time degradation (%)
DT	1	21.8	21.2	2.68	0.3	2.8	4.3	65.41	-34.59
WE	2	6.8	2.0	70.37	4.6	4.7	4.8	58.32	-41.68
NE	3	18.2	13.8	24.31	3.3	3.5	4.3	68.37	-31.63
SE	4	7.0	4.0	42.86	3.1	3.4	4.4	50.46	-49.54

8.7 Conclusions

This study presented a mass evacuation modelling framework that includes a fuzzy logic-based staged evacuation and a dynamic traffic assignment-based evacuation microsimulation model. The staged evacuation model developed in this study assesses the priority needs of vulnerable populations by considering their geophysical, social, and mobility vulnerability for the implementation of a staged evacuation. The novelty of this study is that it develops a sequential modelling system that utilizes a fuzzy logic-based modelling approach to quantify expert opinion and ascertain vulnerability-based prioritization in assessing staged evacuation scenarios within a dynamic traffic microsimulation model.

The study demonstrated the efficacy of the proposed framework with a case study of Halifax, Canada. The prioritization of the planning districts yielded that 'DT' should evacuate first, 'WE' second, 'NE' third and 'SE' last when all three vulnerabilities are considered. The staged evacuation model developed in this study demonstrated a decrease in clearance time for most traffic analysis zones in the range of 0.3-4.8 hours. The improvement in zonal clearance time achieved for 'WE' and 'NE' is in the range of 24.31-70.37%. These two districts are areas of low-income housing and the working population, respectively. It is evident that accounting for vulnerabilities into the prioritization process enables an efficient evacuation of areas that are vulnerable from a social, geophysical and mobility perspective. Simulation results revealed that 'DT' anticipates relatively less improvement in clearance time, which is due to the failure of local intersections and the presence of several densely populated zones in this district. An interesting finding of this study includes that 'SE' ranks last in the vulnerability-based prioritization process but gets evacuated faster. This result can be argued as the inherent transportation system efficiency, well connected and spacious roads, and less traffic volume benefit this district during an evacuation. Moreover, a more disaggregate level analysis showed that there are individuals, who are disadvantaged by a staged evacuation; however, overall network and evacuation performance in all planning districts improved when a staged evacuation is conducted in contrast to a simultaneous evacuation.

This study has several policy implications. The study outlined a process to address different vulnerabilities in the prioritization of evacuees for a mass evacuation. For example, 'DT' has flooding risk, is an area of a high dense population, and has a higher portion of residents with no-vehicle. The consideration of the combined vulnerabilities within the proposed framework identified the priority needs of the 'DT' and considered it to be the first to evacuate. The study also identified traffic operation-related issues as a result of the staged evacuation using the developed traffic microsimulation model. Despite the vulnerability-based evacuation, a staged evacuation could not significantly improve the traffic operation efficiency in DT. This warrants special plans which may include a bus-based evacuation and traffic operation improvement strategies (e.g., specific evacuation routes) to be integrated within staged evacuation planning. Moreover, the prioritization results can be use develop a zoning system and the related maps can be conveyed to all residents through mobile app or the EMO website while the map. The identified areas with priority needs can also be the focal point for the costal engineering and infrastructure protection planning. The appropriate engineering treatment to protect soil, properties, and infrastructure in the identified areas could incentivize the staged evacuation with strong and disaster-resilient built environment.

The study contributes to literature by developing an enhanced staged evacuation modelling framework which will help deal with geophysical, social, and mobility issues together in addressing the priority needs of the vulnerable populations. The results also highlight the significance of a comprehensive assessment of the priority needs of vulnerable populations for a staged evacuation. Although a vulnerability-based prioritization is ensured, evacuation of several zones in the peninsula is not improved. Therefore, this study has been motivated to focus on further countermeasure that could improve the evacuation time and network congestion. The next chapter discusses how all modes of transportation, particularly transit and school buses can be utilized for a mass evacuation.

Chapter 9

Countermeasure: Bus-based Evacuation[6]

9.1 Introduction

This chapter presents an evacuation modelling framework to optimally utilize all available modes, particularly transit and school buses for a mass evacuation process. Typically, mass evacuations rely on automobiles. However, if there needs to be a large-scale evacuation within a short timeframe, all modes of transportation that are available within the network should play a role in evacuating people from the affected area in an efficient manner. Solely auto-based evacuation is not sufficient for a large-scale evacuation, particularly for the evacuation of an urban area with a diverse group of populations. Residents who may lack access to private vehicles (i.e., captive transit riders) or who may choose not to use such vehicles (i.e., choice-based transit riders) during an evacuation may need assistance with transportation (Hess and Gotham, 2007). Moreover, transport network with limited exit points is likely to be grid-locked with a mammoth traffic fleet during an evacuation. Vehicles with high

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[6] This chapter is largely derived from the following peer-reviewed papers:

- Alam, M. J., and Habib, M. A. (2021). Development of an Evacuation Decision Support Tool: A Combined Optimization and Traffic Microsimulation Modelling Approach. Proceedings of the 100th Annual Meeting of Transportation Research Board, Washington, D.C., USA (No. 21-00878)
- Alam, M. J., and Habib, M. A. (2021). A Dynamic Programming Optimization for Traffic Microsimulation Modelling of a Mass Evacuation. *Transportation Research Part D: Transport and Environment* (conditionally accepted)

occupancy e.g., buses can best utilize the network capacity and minimize traffic congestion during such conditions.

Halifax is a historical city that has a quite diverse group of populations and a transport network with narrow roads and limited exit points. The vulnerability assessment in this research reveals wide-ranging socioeconomic characteristics across neighborhoods of Halifax, which highlights the importance of using all modes of transportation, particularly, transit and school buses for evacuation. However, most of the existing evacuation plans across North America rarely address the role of all modes in the evacuation plan. The mass evacuation that resulted from Hurricane Florence in 2018 caused hundreds of thousands of people to use their personal vehicles to evacuate the city, resulting in backed up traffic on I-95 (Wilson, 2018). The estimated automobile evacuation time along the South Carolina Coast during Hurricane Florence was 36 to 48 hours (Marshall, 2018). Moreover, a longer clearance time may cause people to run out of fuel as occurred during Hurricane Rita in 2005 when people were on the roads for 10-12 hours (Blumenthal, 2005). It is evident that auto-only evacuation may create severe traffic congestion, particularly in Halifax due to the inherent network design problem. Therefore, it demands the development of a countermeasure that considers transit and school buses in combination with other available modes in the network for optimizing traffic compositions and consequently, improving mass evacuation process in terms of traffic congestion and evacuation times. The challenge with optimally utilizing all modes during an evacuation is that how to allocate buses while both the demand and the populations' vulnerability require equal attention. Furthermore, many cities do not have adequate supply of buses to move all low-mobility evacuees (Wolshon et al., 2005), which urges to evaluate if the existing transit fleet is adequate to transport the target population. Otherwise, school buses may need to be considered to increase the fleet capacity depending on the demand. That being said, it needs a systematic process to determine the optimum composition of auto-bus mix in the network.

This study develops an evacuation modelling framework that considers all modes for evacuation and optimally allocate buses to evacuees based the vulnerabilities that they are exposed to. Therefore, the objectives of this study are to (i) develop an agent-based all mode allocation module (AMAM) accounting for the vulnerabilities that the evacuees are exposed to and the mode-specific capacities, and (ii) utilize a traffic evacuation microsimulation model to feed the AMAM with information regarding network supply sufficiency (i.e., bus capacity) to facilitate optimization process. The proposed optimization process formulates a dynamic Knapsack problem (Pan and Zhang, 2018) where bus capacity represents the component "Knapsack" and vulnerability is the component to be maximized. A vulnerability score comprising of social and mobility vulnerability measurements is utilized to demonstrate the degrees of individuals' exposures to vulnerabilities. The maximization of the vulnerability scores indicates that people with a higher exposure to vulnerabilities are prioritized for bus allocation. A Dynamic Programming algorithm is used to solve the Knapsack optimization problem within a Python platform. The optimization process is iterated to test and evaluate alternative scenarios within AMAM and the traffic evacuation microsimulation model. The results from this research will help emergency professionals to identify the optimum resource allocation plan for an efficient evacuation following an iterative approach. The results are particularly useful when any empirical evidence or training data on optimum composition of auto-bus mix in the network is limited due to the impossibility of observing an evacuation event and/or conducting a mass evacuation drill. The scenario testing within traffic evacuation microsimulation model demonstrates an improvement of overall evacuation performance measures in terms of network clearance time and the performance of traffic flow indicators.

9.2 Literature Review

Auto-based evacuation studies are abundant in the existing literature and have been enriched over the past few years. Many studies identified challenges with auto-based evacuation, and proposed improvement strategies (Abdelgawad and Abdulhai, 2009; Ng and Waller, 2009; Wolshon, 2002; Urbina, 2002) to make evacuation operations efficient and safer. During the 2005 Hurricane Katrina in New Orleans, the evacuation primarily relied on automobiles. The evacuation plan implemented for this hurricane did not develop a plan for the use of all modes, including public transit and school buses. As a result, a mammoth auto traffic fleet created unprecedented traffic congestion. This caused vehicles to run out of fuel due to long clearance times (i.e., approximately 20 hours), and it left many people, including the transit-dependent population, with no option but to stay at home. The estimated number of buses required to evacuate New Orleans was 2000 but the city only had 500 transit and school buses available. Due to a lack of proactive and effective planning, the evacuation for Hurricane Katrina was not as successful as it should have been (Litman, 2006).

Existing evacuation literature has discussed the planning for and modelling of auto-based, and multimodal evacuations. In the case of evacuations involving buses, public transit was mainly used for evacuating the vulnerable population who do not have cars or other options for evacuation. Although transit is not predominantly considered in evacuations, individuals who willingly choose buses or need to use buses as their method to evacuate have never received attention in literature. Since Hurricane Katrina, several studies shed light on how to evacuate transit dependent and carless populations using public transportation. These studies focused more on the bus operations, trip sequences and fleet sizes. Bolia (2019) developed an optimization model to determine the number of bus trips and bus trip sequences to evacuate a known demand in response to a disaster. The study was not meant to formalize how to allocate any available mode, including buses to whoever needs them by any logical means. Instead, the study solely focused on transit network operation in the network. The study solved a transit network design problem by considering uncertainties including bus failure amid evacuation. Khulshretha et al. (2014) and Alam et al. (2019) developed optimization models to enhance multimodal evacuations by optimizing pick-up locations and bus routes. Cavusoglu et al. (2013) developed a simulation model that operated through two scenarios, one which considered transit-dependent populations, and one that did not. The objective of the study was to evaluate network performance during evacuation while considering both vehicle and transit operations. It was discovered that average travel speed reduced, and delays increased. The general purpose of this study was to explore potential impacts that may result from the evacuation of the vulnerable population, however, the evacuation scenario that utilized buses to evacuate the carless population experienced no changes in terms of traffic impacts. However, there is a significant gap in knowledge regarding the demand for buses due to evacuees' exposure to different vulnerabilities, including social and mobility vulnerability.

The aforementioned studies address several topics: challenges associated with auto-based evacuation, transportation needs of the transit-dependent and carless populations, and the service requirements for a transit operation during an evacuation. What are not adequately addressed in these studies include (i) access to all transportation modes for all evacuees so that they can choose specific modes to meet their needs or accommodate for uncertainties that may appear during evacuation, and (ii) the optimum composition of auto-bus mix in the network to achieve an efficient transport network for evacuation. Lessons learned from Hurricanes Katrina and Rita highlight the significance of involving all modes in evacuations. Evacuation plans must account for all evacuating modes, including automobiles and buses available in the network (Wendell, 2020). Otherwise, the sudden spike in traffic demand may create large-scale congestion. Consequently, should it be either vehicular traffic or buses, could be stranded on the road as it occurred in Houston during the evacuation due to Hurricane Rita (Renne et al., 2008; Zhao et al., 2010). Literature review clearly indicates that there is a major gap in understanding how to formalize an optimum auto-bus composition for an evacuation when there are concerns regarding the number of buses and the vulnerability considerations within the evacuation planning process.

This study fills this gap by developing a novel framework to utilize all modes in an evacuation and to estimate an optimum composition of auto-bus mix that demonstrates improvements in the network performance during an evacuation. The study formulates and solves a mode allocation problem while the entire evacuation demand must be evacuated, and the mode-specific capacities are respected. There is always an ethical dilemma in how to allocate resources during an emergency. It is of utmost importance that resource allocation addresses the urgency of each evacuee. For example, evacuees exposed to a higher degree of social or mobility vulnerability should be prioritized for bus allocation. That being said, one's vulnerability status may or may not be related to personal vehicle ownership. This research utilizes a score to explain the exposure of evacuees to different vulnerabilities, including mobility vulnerability obtained from the traffic microsimulation model used in this study.

Broadly, the resource allocation problem for an evacuation involves two components such as demand (resource receivers/evacuees) and resource constraints (e.g., bus capacity) that change with the progression of evacuation time. When demands and the measurements of evacuees' exposure to vulnerabilities at different evacuation times are given, the resource allocation (e.g., bus allocation) is then a combinatorial optimization problem. The optimization process finds an optimum set of demand for bus allocation while ensuring that individuals with higher vulnerabilities are prioritized and the bus capacity is optimally utilized. Several widely used combinatorial optimization problems include the Traveling Salesman, Vehicle routing, and Knapsack problems. Knapsack problem involves maximizing the number of items (e.g., evacuees) and item values (e.g., vulnerability scores) while the Knapsack capacity (i.e., bus capacity) must be satisfied. The proposed optimization problem in this study completely assimilates to the Knapsack problem of combinatorial optimization. Knapsack is a widely known NP-complete problem and there is no known polynomial solution algorithm to solve this nature of problem which is fast and exact (Cormen et al., 2009; Welch, 1982). There are several solutions that can solve NP-complete problems in polynomial time, including Brute Force method, Dynamic Programming, Branch and Bound algorithm, Branch and Cut algorithm, and Greedy algorithm (Hristakeva and Shrestha, 2005). Brute Force is a straightforward problem-solving algorithm which systematically enumerates all possible combinations (2^n) of the target items and identifies one with the maximum value. 2^n is the total combination as there are two options for each of the n items: accept or reject. Thus, the complexity of this algorithm grows exponentially following $O\left(2^n\right)$. Due to complexity, this algorithm is suitable for small instances of Knapsack problem, while very often evacuation involves a larger optimization problem. Other abovementioned algorithms have their own advantages. Branch and Bound can solve some large optimization problems due to its capability to discard a subset of the solution set even before its construction if it cannot generate a solution within the estimated lower and upper bounds in the optimal solutions. Nonetheless, it still suffers from exponential complexity (Hristakeva and Shrestha, 2005; Goerigk et al., 2014). However, Dynamic Programming (DP) algorithm appears to be more suitable for solving a Knapsack problem. DP is efficient to deal with the problems involving re-occurrence of sub-problems. It computes a sub-problem only once and stores the value in a table for later use. Thus, the algorithm efficiently reduces computation time by avoiding the solving of recurrent sub-problems each time. Therefore, this study adopts a Dynamic Programming algorithm for solving the proposed combinatorial optimization problem. DP can efficiently be used until the capacity is less than the demand, which represents an evacuation condition. This study improves the solution approach using DP for solving a large-scale evacuation optimization problem while algorithms used in solving other large-scale evacuation problems (Alam et al., 2019; Kulshrestha et al., 2014; Goerigk et al., 2014) may suffer from exponential complexity or local optima.

The study establishes a feedback loop between optimization and traffic microsimulation models where optimization results are used in a traffic microsimulation model to determine whether any improvement in evacuation operations is achieved and/or if the fleet capacity is exhausted. Traffic microsimulation model updates the optimization module with this information to facilitate further testing of sequential scenarios. The iterations for testing sequential scenarios can be terminated upon achieving one or both criteria mentioned above. The proposed all mode evacuation strategy will help emergency managers and professionals iteratively evaluate contrasting evacuation scenarios considering all modes and make an informed optimal decision.

9.3 Methodology

This study develops a framework of an all-mode evacuation which accounts for evacuees' exposure to different vulnerabilities and bus fleet capacity in the vehicle allocation process for a mass evacuation. The proposed framework involves a combined vehicle allocation and traffic evacuation microsimulation model. This framework allows emergency professionals to iteratively investigate whether the available vehicle fleets can accommodate the entire evacuation demand if the demand is optimally assigned to all available modes. The tool enables evaluating alternative scenarios using a feedback loop between vehicle allocation and the traffic microsimulation model, following an "if-else" mechanism. Therefore, the methodology of this study is two-fold: (i) development of an all mode allocation module (AMAM) that follows a "Knapsack optimization" and adopts a solution algorithm "Dynamic Programming" to prioritize individuals with higher levels of vulnerabilities for bus allocation and optimize the use of limited bus capacity, and (ii) utilizing the traffic evacuation microsimulation model to simulate all mode evacuation scenario and update AMAM with bus capacity information for sequential scenario testing and evaluation. The study uses a score system to estimate the degrees of evacuees' exposure to social and mobility vulnerabilities. The social vulnerability score for each individual is obtained from a Bayesian Belief Network-based vulnerability assessment model (Alam and Habib, 2019a). The mobility vulnerability is estimated in terms of the amount of average time required to travel from an origin zone to destination shelters. The traffic microsimulation model calculates the travel time between origin and destination for each individual using auto in the network. Individuals are selected from a synthesized population of Halifax obtained from integrated Transport Land Use and Energy (iTLE) modelling system (Fatmi and Habib, 2018). **Figure 9-1** presents overall framework of the proposed all mode evacuation model.

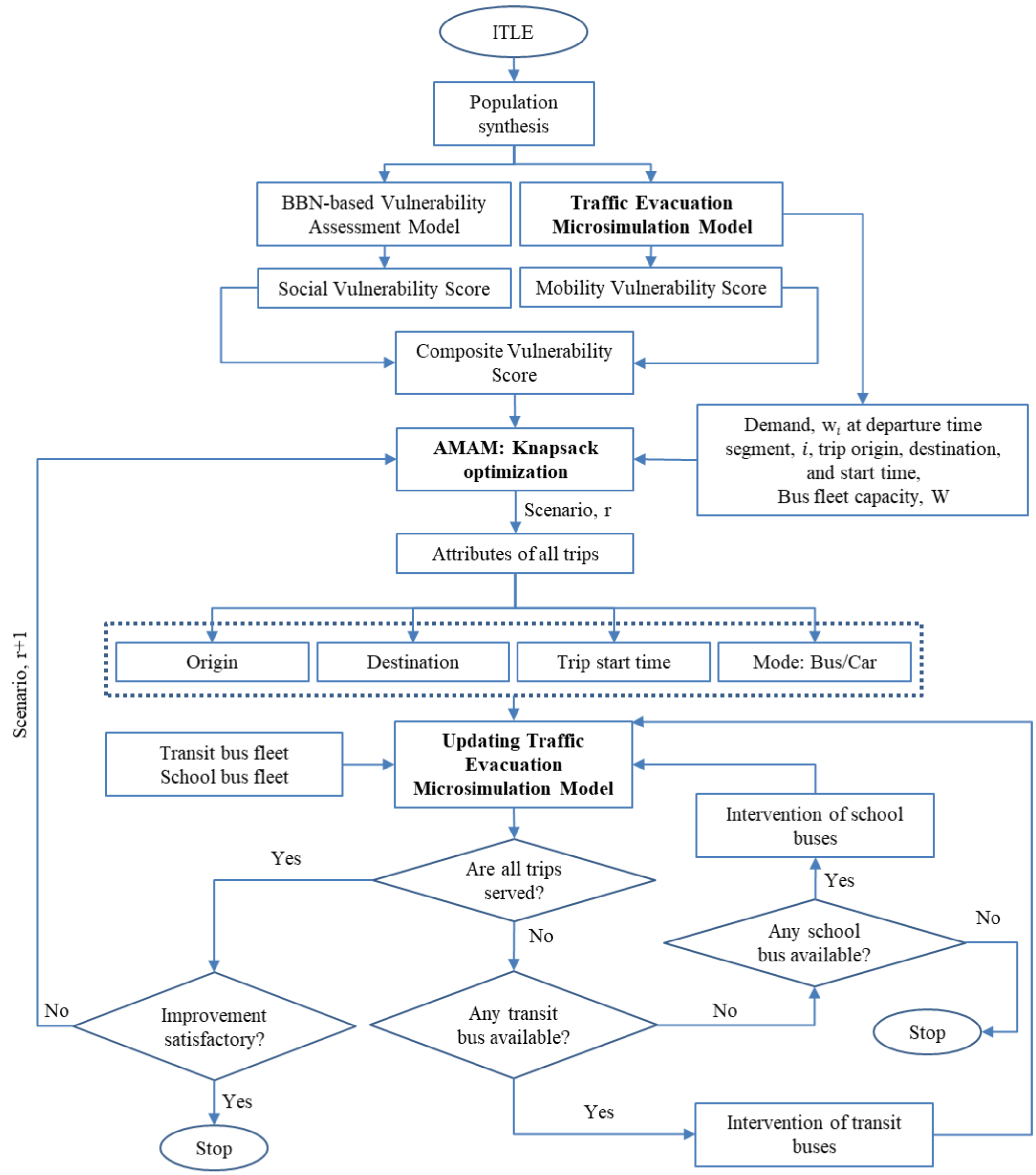

Figure 9-1 Evacuation modelling framework for bus allocation

9.3.1 Knapsack Problem Formulation

This study formulates a combinatorial optimization problem called "Knapsack problem", that aims to best utilize the available Knapsack capacity (i.e., bus capacity), while prioritizing the maximum number of vulnerable evacuees for bus allocation. Let W represents bus capacity and I represent a set of individuals attributed by departure time segment i. Each time segment, i

contains a certain number of individuals denoted by w_i. Each time segment, i is characterized by a score, v_i reflecting individuals' exposure to vulnerabilities within that time segment. The optimization can then be formulated as follows:

Objective:

$$max \sum_{i \in n} v_i \tag{1}$$

Subjected to:

$$\sum_{i \in n} w_i \leq W \tag{2}$$

i, w_i as integer and $, v_i$ as double or integer

$$i = \{0,1,2,3.......,n\} \tag{3}$$

Knapsack problem is a NP-complete optimization problem, and no exact and fast algorithm is known to solve Knapsack in polynomial time. This study follows dynamic programming (DP) algorithm to solve the stated optimization problem. DP is a technique to design and implement an algorithm that disaggregates a large optimization problem into smaller sub-problems. DP can efficiently be used until the capacity is less than the demand, which represents an evacuation condition. The uniqueness of this algorithm is that it stores the solution of sub-problems for recursive use in later time.

9.3.1.1 Dynamic Programming Algorithm for Sub-Problem Formulation

Dynamic programming algorithm develops a matrix, K with a dimension of $n+1$ rows and $W+1$ columns, where solutions to sub-problems are subjected to memorization for later use repeatedly. Each cell (i, j) of the matrix, K represents the total Knapsack value that is calculated by including a subset of individuals preceding the current group in time segment i while not exceeding the Knapsack capacity. The obtained Knapsack value at this point may result from including or not including the current group of individuals. Note that the first row and column of K are set to zero. Then, the formula to determine the solutions to sub-problems starting from top-left corner to right-bottom corner of the matrix can be identified as follows:

$$K[i][w] = K[i-1][w], \text{ when } w_i[i] > w \tag{4}$$

$$K[i][w] = \max[K[i-1][w], K[i-1][w-w_i[i]] + v_i], \text{ when } w_i[i] < w \tag{5}$$

$$K[0][w] = 0 \text{ , and } K[i][0] = 0 \tag{6}$$

$$w = \{0,1,2,3.......,W\} \tag{7}$$

Finally, the values corresponding to $K[n][W]$ represents the Knapsack value calculated through assigning buses to individuals exposed to higher vulnerabilities without exceeding the bus capacity. This value represents the optimal value to the original Knapsack problem. The last thing this study has added to the formulation of the dynamic programming algorithm is a function to track individuals in different time segments that contributed to the optimal solution. This function starts tracking individuals using the value at $K[n][W]$ and ends at $K[0][0]$. Individuals, w_i at time segment i are considered in the Knapsack solution if the following condition is met:

$$K[Rows][Column]! = K[Row-1][Column] \text{ where, Row} = n \text{, and Column} = W \tag{8}$$

If the condition is met, the function proceeds to the preceding group of individuals by shifting the cell to (Row-1, Column - $w_i[i]$). The process continues until it reaches $K[0][0]$.

9.3.2 Traffic Evacuation Microsimulation Model

This study utilizes a traffic microsimulation model developed in Chapter 4 and Chapter 5. The model includes a transport network that considers all available modes for the evacuation of the Halifax Peninsula. Transit network consists of bus routes and marshal point locations as shown in **Figure 9-2** and **Figure 9-3**. The model includes twelve transit routes and 135 bus stops obtained from Chapter 5.

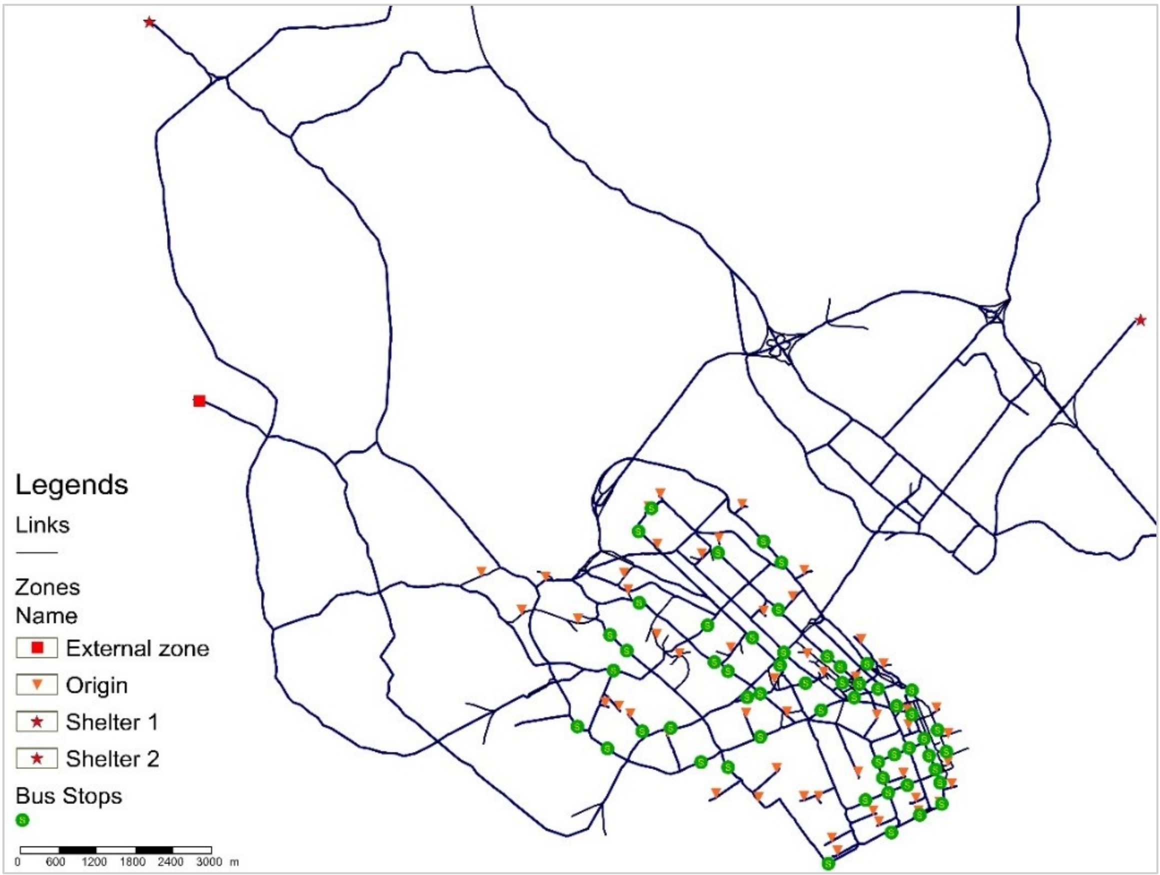

Figure 9-2 Road network elements of Halifax transport network, including bus stops in traffic microsimulation model

Figure 9-3 Bus routes obtained from the MILP optimization model in Chapter 5

9.4 Scenario Testing and Evaluations

This study comprehensively tests scenarios of mass evacuation on the Halifax Peninsula, and demonstrates the benefits of using all modes, especially buses for evacuation. The study develops countermeasure scenario that allocates buses to accommodate for different levels of demand based on population vulnerabilities and available bus capacity. Four scenarios are developed where buses are allocated to an incremental demand across scenarios to gradually improve evacuation times and network performances. Individuals who do not have cars are assigned to buses by default for evacuation. The optimization is conducted to identify auto users for bus allocation based on their urgency. To develop sequential scenarios, this study assumes the first scenario, which considers 5% of auto users for bus allocations. If further evacuation improvements are needed and if there is still bus capacity left that can be utilized for accommodating more individuals, the AMAM performs further iterations for testing successive scenarios. The study increases the percent demand for bus allocation by 5% for successive scenarios. Four sequential scenarios are considered for the evaluation: (i) Scenario 1 – 5% demand, (i) Scenario 2 – 10% demand, (i) Scenario 3 – 15% demand, and (i) Scenario 4 – 20% demand. Each scenario is implemented within the AMAM to identify the successful individuals that are assigned to a bus. The AMAM takes information from multiple sources to perform optimization such as time-varying bus capacity from traffic microsimulation model, vulnerability scores from Bayesian Belief Network-based vulnerability assessment model, and simulation results. The simulation results for the four scenarios are evaluated and compared with respect to a base case scenario. Base case scenario represents the evacuation by auto and transit while transit is used to only evacuate people who do not have cars or other options for evacuation.

9.5 Results and Discussion

9.5.1 Overall Scenario Results

The proposed framework first serves the target demand using a fleet of 322 buses that Halifax Transit owns. There are also around 380 school buses in Halifax. If the transit fleet capacity is exhausted in a scenario, school buses are called within the traffic microsimulation model. **Table 9-1** lists all sequential scenarios tested and evaluated using the framework. All scenarios are compared to a base case scenario that uses buses for only evacuating transit-dependent population. The results from the scenario analysis reveal that traffic congestion can be improved by a reduction of vehicular traffic of 3.9-7.7% from the network if 5-20% of the auto evacuation demand are served by buses. **Figure 9-4** illustrates the improvement in queue length due to the implementation of the proposed scenarios. The queue length results suggest that with the increase in the number of individuals allocated buses from scenario 1 to scenario 4, traffic congestion, including queue length significantly decreases on major key arterial streets as shown in **Figure 9-4a** to **Figure 9-4d**. The improvement in congestion is also reflected in evacuation clearance time which anticipates a reduction of 9-22.7% with respect to a base case scenario. **Figure B-7 – Figure B-9 in Appendix B** also present the improvements in clearance time across all TAZs under the proposed evacuation scenario. The results suggest that except for scenario 1, municipal bus capacity is exhausted while the proposed AMAM utilizes school buses to accommodate the respective demand for evacuation.

Table 9-1 Results for Bus-based evacuation

Scenarios	Demand assigned to buses	Required transit bus	Required School bus	Vehicle traffic reduction w.r.t base case, %	Clearance Time improvement w.r.t base case, %
Scenario 1: 5% demand	8,725	193	0	3.9	9.0
Scenario 2: 10% demand	14,900	322	5	4.7	13.6
Scenario 3: 15% demand	18,150	322	34	5.5	18.1
Scenario 4: 20% demand	21,400	322	88	7.7	22.7

The results in **Table 9-1** will assist decision makers in selecting one of the scenarios to be implemented. For example, one may select scenario 4 with the highest improvement in evacuation time, but with a large cost to deploy 410 (= transit bus-322+school bus-88) buses. They may also select scenario 1 which only involves 193 municipal buses but demonstrates a relatively small improvement in terms of evacuation time. In total, 410 buses are used in the highest demand scenario, while there are 702 buses (= 322 buses of Halifax Transit + 380 School buses) available indicating that more individuals can be served by the remaining fleet capacity. Decision makers can easily evaluate municipal budget and the available lee way time to safely evacuate people when choosing a scenario.

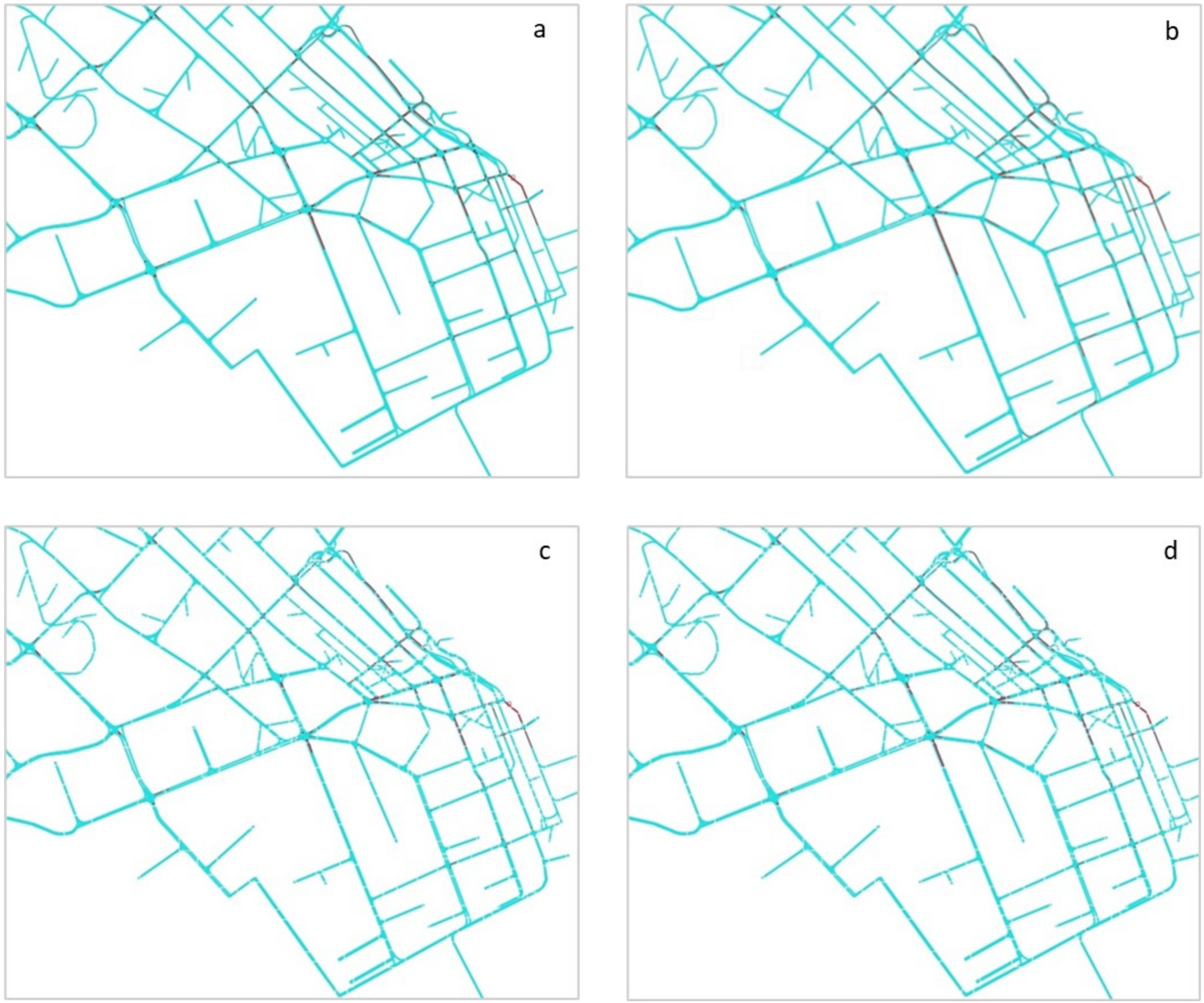

Figure 9-4 Average queue length measured in four vehicle allocation scenarios where (a) Scenario 1- 5% demand, (b) Scenario 2- 10% demand, (c) Scenario 3- 15% demand, and (d) Scenario 4- 20% demand

9.5.2 Prioritization Accounting for Vulnerabilities

The proposed bus allocation process in this study prioritizes individuals according to their estimated vulnerabilities. The vulnerability score for an individual is calculated by the aggregation of scores for social and mobility vulnerability. All vulnerability scores are used to develop twenty classes with an interval of 0.05: V1 being the first and the lowest scored class and V20 being the last and the maximum scored class. **Figure 9-5** shows the percent individuals that are assigned to a bus while accounting for different vulnerabilities.

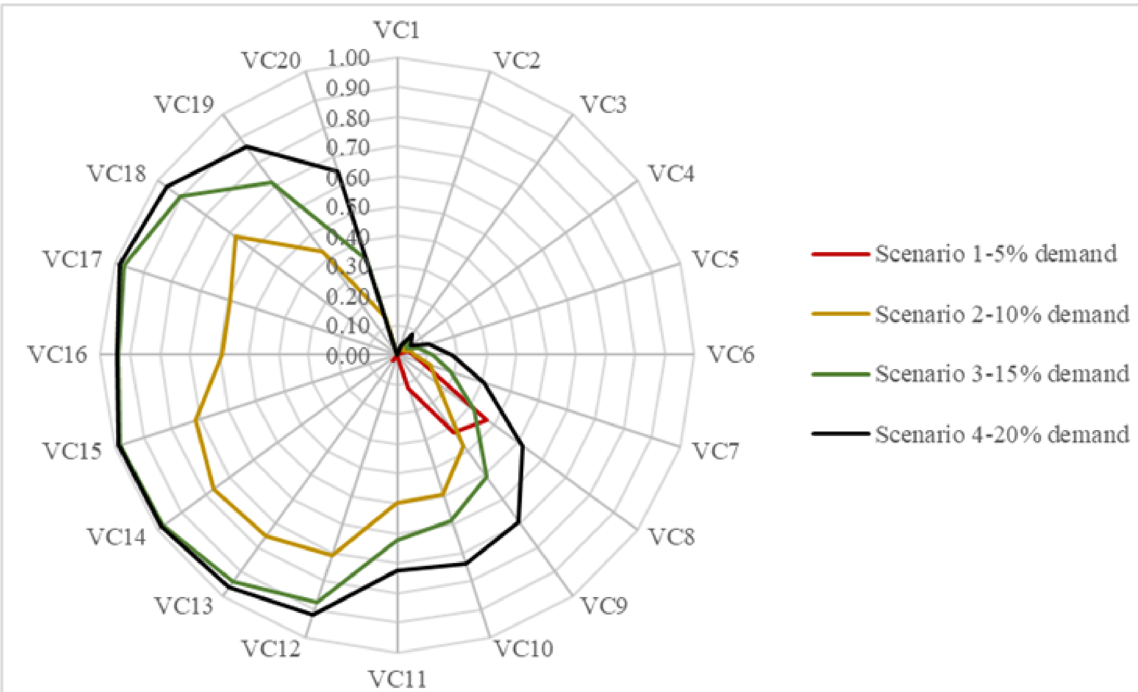

Figure 9-5 Percent individuals assigned to buses based on different vulnerabilities

The results suggest that the percent individuals prioritized across zones for bus allocation comprise of a large group of individuals with relatively higher vulnerabilities, a category of V12 or above, in almost all scenarios, which supports the objectives of this study. Scenario 3 (15% demand) and scenario 4

(20% demand) show a similar pattern in bus allocation for individuals within the category mentioned above. The percent individuals that are assigned to a bus within this category are relatively higher and similar in both scenarios. Scenario 1 represents a 5% auto-based demand that is shifted to buses for evacuation. The proposed method intends to evacuate as many vulnerable people as possible by buses; that being said, a small size of 5% demand does not reflect the entire vulnerable population. The results suggest that it requires at least a 10% demand consideration to reflect a reasonable distribution of vulnerable population when allocating buses to evacuees from a wider area for evacuation.

9.5.3 Addressing of Vulnerabilities across Planning Districts

The study area has been sub-divided into four planning districts "Downtown (DT)", "West-End (WE)", "North-End (NE)", "South-End (SE)" for analysis purposes. **Figure 9-6a** and **Figure 9-6b** show the vulnerability scores of individuals of different planning district who are assigned to buses for their evacuations in scenario 3 and scenario 4, respectively.

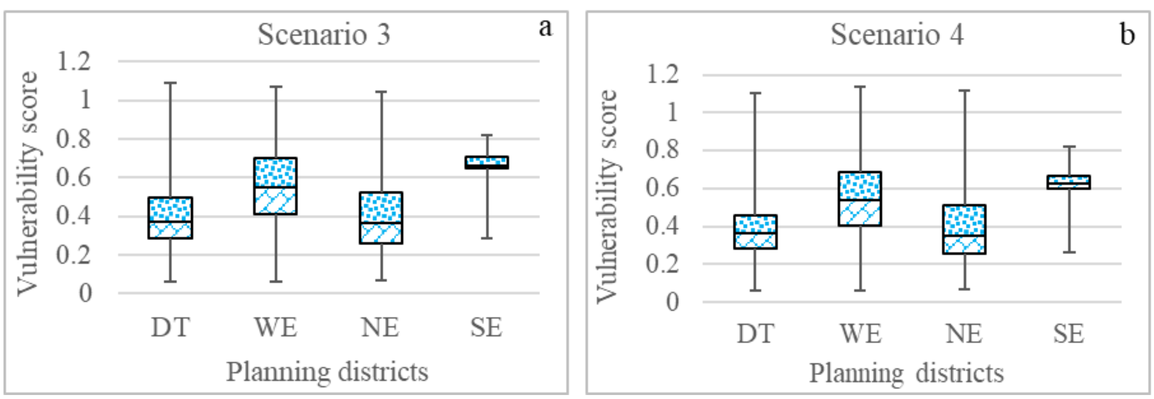

Figure 9-6 Addressing vulnerabilities across planning districts for bus allocations in (a) scenario 3-15% demand, and (b) scenario 4-20% demand.

Scenario 1 and scenario 2 serve a smaller demand and do not encompass all planning districts while prioritizing individuals with more vulnerabilities. For example, scenario 1 with a target demand of 5% only prioritizes individuals from DT for bus allocation. The results suggest that the only difference between **Figure 9-6a** and **Figure 9-6b** is that the upper whisker in **Figure 9-6b** is relatively longer in the case of NE and WE. The reason being is that in scenario 4, due to increase in the target demand, more people from different zones become eligible for bus allocation based on their urgency.

9.5.4 Critical Time Identification for Bus Allocation

This study identifies the critical time segments of an entire evacuation period for bus allocation to improve overall evacuation operations. **Figure 9-7a** to **Figure 9-7d** illustrates the time segments when individuals have been assigned to buses.

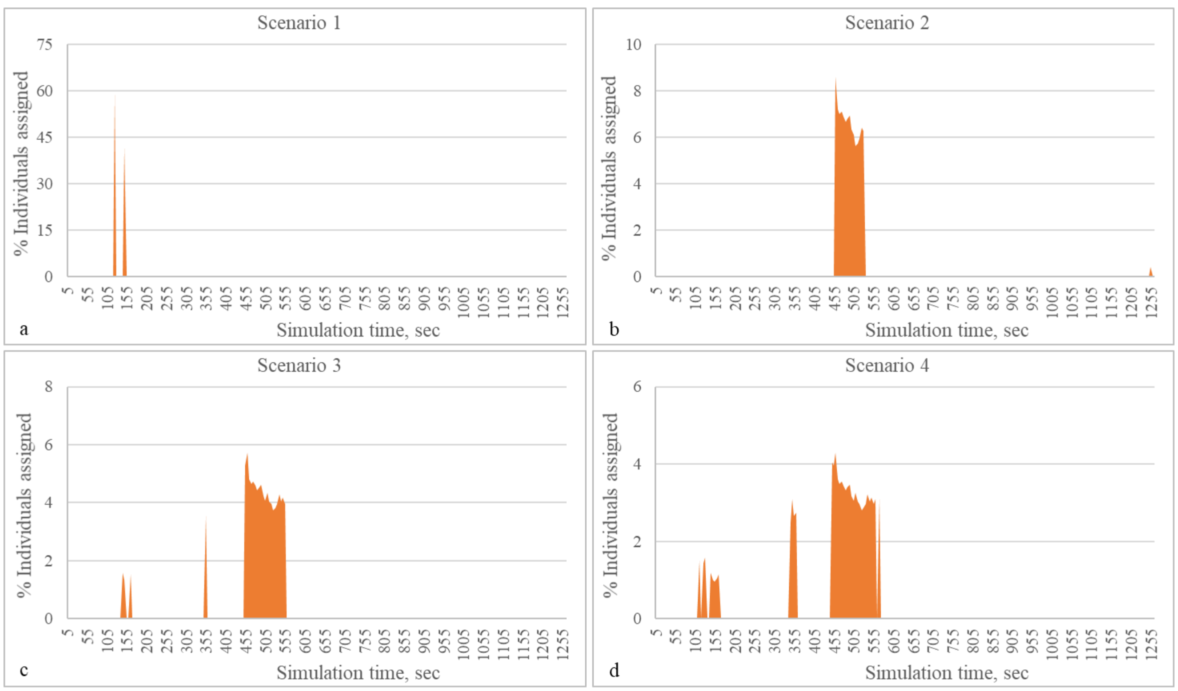

Figure 9-7 Time segments of an evacuation period that assigns buses to individuals under four scenarios (a) Scenario 1 –5% demand, (b) Scenario 2 – 5% demand, (c) Scenario 3 – 5% demand, and (d) Scenario 4 – 5% demand.

In the case of a smaller demand for bus evacuation, for example in scenario 1 (5%) and scenario 2 (10%), bus allocation in a single time segment is found sufficient (see **Figure 9-7a** and **Figure 9-7b**). On the other hand, in the case of scenario 3 (15%) and scenario 4 (20%), buses were allocated to individuals at different time segments to encompass a larger demand from a wider area. The results have certain policy implications. It helps decision makers to identify the critical time segments of an evacuation. For example, when individuals need transportation assistance the most and how effectively the demand can be accommodated given the limited capacity of buses.

9.6 Conclusions

This study presented a novel framework of an all-mode evacuation modelling that includes an All-Mode Allocation Module and a traffic evacuation microsimulation model. The contribution of this study is that it recognizes transit and school buses in evacuation operation and optimizes the composition of auto-bus mix in the transport network. Methodologically, the study contributes to solving bus allocation optimization problem by implementing a Dynamic Programming algorithm. In contrast, several solution algorithms used in other evacuation related integer and mixed integer linear programming problems may suffer from local optima or exponential complexity. This study also provides a comprehensive approach of mass evacuation microsimulation modelling and scenario testing.

The study considered a case study of Halifax, Canada to demonstrate the efficacy of the developed countermeasure scenario in meeting the transportation needs of the entire population of the Halifax Peninsula, while simultaneously ensuring an improvement in evacuation time. Four sequential scenarios representing different levels of demand for bus allocation were evaluated within the developed tool. The results show that individuals with higher degrees of vulnerabilities are prioritized for allocating evacuation buses in case of all scenarios. The developed tool has the capability to identify the critical time segments of an entire evacuation period for bus allocation to improve overall evacuation operations. Moreover, if the bus fleet is large enough to accommodate a significant proportion of evacuation demand, for example, 15% and 20% in this case, a vehicle traffic reduction of 5.5%-7.7% is achievable. This results in a potential reduction of evacuation times by 18.1%-22.7%. All scenarios tested and evaluated demonstrate an improvement in clearance time and network performances. The simulation results reveal that a reduction of 9-22.7% in clearance time is obtained if the available bus capacity can accommodate 5% to 20% of auto-based evacuation demand. The transport network is also found to exhibit an improvement in traffic congestion. Queue length on major evacuation routes is found to decrease in all scenarios. In summary, the results from all mode evacuations scenario support the objective of this study and the rationale of developing an evacuation strategy that recognizes the role of all modes in evacuation operations.

The study addresses the gaps in evacuation literature by considering and implementing the roles of all modes, particularly transit and school buses in evacuation operations. The proposed modelling approach in this study has the potential to assist emergency personnel in their decision-making process by enabling them to design and test alternative evacuation scenarios including resource allocation and management problems when considering a large-scale mass evacuation.

Chapter 10

Conclusions

10.1 Summary of the Research

The development of a mass evacuation decision support tool has emerged from the need to consider different types of traffic disruptions and uncertainties in assessing evacuation scenarios. Majority evacuation simulation studies explore evacuation times and traffic congestion for evacuation scenarios ignoring the potential impacts of traffic disruptions and the risk occurrence. Without considering this aspect, the evacuation scenario may not represent the actual evacuation conditions and the analysis may underestimate the clearance time and the traffic congestion in the network. This study contributes to a large-scale traffic microsimulation modelling that incorporates multiple modules for a greater representation of uncertainties and risks associated with mass evacuation processes. The further research gaps are identified through the review of countermeasure literature. Literature review suggests that the existing countermeasure modelling predominantly focuses on the traffic congestion improvement; however, lacks in addressing the vulnerable population and their priority needs in the implementation process. The prioritization of the vulnerable population for evacuation further creates ethical dilemma and requires a systematic prioritization process that holistically assess geophysical, social and mobility characteristics. Furthermore, the existing countermeasure studies undermine the potential advantages of using all modes for evacuations. Further evacuation modelling needs to consider all available modes particularly transit and school buses to meet the transportation needs of all and simultaneously improve the evacuation times and network congestion.

The study starts with developing of a large-scale traffic evacuation microsimulation model which includes a dynamic traffic assignment module to manifest drivers' route choice decisions in a heavily congested transport network during an evacuation. This research is first of its kind which combines a flood risk and a traffic simulation model to inform evacuation scenario building process considering traffic disruptions due to floods of different extremes. Three flooding events such floods of a water level 2.9m, 3.9m, and 7.9m CGVD28 resulted in three level of network disruption scenarios in this study. Note that among scenarios, 7.9m flood scenario refers to a long-term extreme weather conditions in future and is unlikely as it is based on the 100-year sea level rise prediction. The results from the simulation suggest that the network disruption due to the flooding of links or exit points may lead to a prolonged and/or an incomplete evacuation. In the case of a flood of 7.9m water level, only 87% evacuation is completed due to 31.2% reduction of evacuation routes in the network. The results from this research indicate that coastal cities with limited exit points are vulnerable due to the possibility that one or more exit points may undergo water and the subsequent impacts can be as significant as found in the case of the Halifax Peninsula.

Initially, the traffic simulation model was auto based. The study develops an evacuation transit network that consists of specific bus routes and marshal point locations. The study develops an optimization model that follows an advanced solution algorithm to determine optimum transit routes and marshal point locations. The solution approach is derived from the combination of two separate solution algorithm, which demonstrates an improvement in the quality of solutions and the computation time compared to that of each independent process. The identified transit network skeleton is coded within the already developed traffic microsimulation model. The simulation results reveal that bus has adaptive capacity to accommodate for not only the transit-dependent population but also those who may not choose private vehicles as their methods for evacuation or shift from other modes to transit.

Besides considering natural disaster related network disruption risks, the developed MEDS tool addresses further complexities associated with evacuation operations within the traffic microsimulation model. The simulation model explicitly incorporates a collision prediction model developed through a combined Bayes theory and Monte Carlo simulation approach that identifies the collision hotspots and calculates collision probabilities during an evacuation. Vehicle collisions are generated at the hotspots within the microsimulation model utilizing a collision generation module. The analysis of evacuation scenarios considering uncertain network disruptions reveals that it may increase the clearance time up to 50% in the worst-case scenario compared to an undisrupted evacuation operation. This study has considered a worst-case scenario demonstrating five concurrent collisions at five hotspots in the network. Simulation results regarding staggered disruptions reveal that it takes at least 23 hours for a complete evacuation if the traffic disruption is removed in 2 hours or less. The evacuation time turns out to vary within 23-31 hours if the disruption is removed within 2-24 hours for a concurrent collision occurrence scenario.

The mass evacuation decision support tool is leveraged to test and evaluate totaling for twenty evacuation scenarios; one refers to base case scenario and the rest consider multi-layer complexities and implement countermeasures for assessing mass evacuations. The overall analysis of evacuation scenarios reveals that it may take 22-33 hours for the evacuation of the Halifax Peninsula depending on the nature and the severity of disruptions. The range of the evacuation times can be used by the emergency professionals in Emergency Management Office (EMO) or in other agencies for evacuation planning, including preparedness, response, and developing policies.

The MEDS tool is further utilized to conduct a zonal vulnerability assessment in the context of a mass evacuation. The vulnerability assessment in this study follows a Bayesian Belief Network modelling approach. The model identifies the factors affecting vulnerability and captures the causal relationships across different elements of the vulnerability. The study also quantifies the influence of the factors on the respective vulnerability on a spatial dimension through a parameter sensitivity analysis. For example, the factor 'large household' and 'no vehicle ownership' are two key determinants affecting Downtown's vulnerability during an evacuation. The vulnerability assessment provides insight into the potential areas that may require special evacuation assistance. The vulnerability assessment results can also be the basis for a zonal demarcation which further assists in prioritized evacuation.

The evacuation modelling tool also implements five scenarios that test two countermeasures, namely staged and bus-based evacuation. The comprehensive scenario analysis helps understand the challenges associated with evacuation, the potential traffic impacts, the process to identify the appropriate countermeasures and the implementation techniques. In the existing studies, contraflow operation has been significantly researched and demonstrated significant increase in network capacity. Researchers claimed a significant network performance improvement along the highway. A strategic level countermeasure such as staged evacuation is not adequately explored in the existing literature. Furthermore, it lacks a systematic process to address the priority needs of the vulnerable population. This study developed a staged evacuation model that prioritizes areas under the riskiest conditions. The study follows a fuzzy logic approach to ascertain a vulnerability-based prioritization in this study. The prioritization results suggest that DT is to be evacuated first followed by WE, NE, and SE considering the combined effects of geophysical, social, and mobility vulnerability. It has been observed that the staged evacuation yields a reduction of 2.68 – 70.37% in clearance time for four planning districts in the Halifax Peninsula. Although, staged evacuation modelling in this research ascertains a vulnerability-based prioritization, there are some areas that received less improvement in terms of network and evacuation performances. The staged evacuation scenario analysis suggests that staged evacuation may not always work better for certain geographic locations, network configurations and population density. A special plan for example, bus-based evacuation may need to be integrated to effectively use staged evacuation. To explore further countermeasure, the study develops an optimization problem to utilize all transportation modes in evacuation. Evacuees are assigned to buses based on the vulnerabilities that they are exposed to. The study formulates the bus allocation problem following a Knapsack optimization technique. It enhances the solution approach for solving Knapsack problem by utilizing dynamic programming. The bus-based evacuation modelling in this study offers promising results. Simulation results revealed that a reduction of 9-22.7% in clearance time is achievable if the available bus capacity can accommodate for 5% to 20% of auto-based evacuation demand. Using the results as the benchmark, decision makers can easily evaluate municipal budget and the available lee way time to safely evacuate people when choosing from different bus demand scenarios.

In summary, the mass evacuation decision support tool provides a flexible platform for coupling multiple modules that mutually communicate with necessary information through different evacuation parameters for a holistic analysis of a mass evacuation. The tool is the first of its kind as it combines multiple modules to address uncertainties and risks associated with a mass evacuation which are very often overlooked in the analysis and evaluation of evacuation scenarios. The tool is useful as it enables countermeasure scenario building process and can be used by emergency professionals to understand what types of strategies are effective, how to plan countermeasure implementation process and what are the potential consequences associated with countermeasure implementation. The developed MEDS tool is also transferable to assess evacuation scenarios in other areas as the information required by the modules are readily available in almost all other jurisdictions. For example, MEDS tool utilizes information from a regional transport network model, collision data, population synthesis and others. Particularly, the tool will be effective to plan evacuations using all modes available in other areas as it offers the flexibility to include additional modes of transportation within the evacuation plans. The tool can also be used for smaller community evacuations which would require to consider the household as the smallest spatial unit for trip production in the simulation. Even the evacuation of a concentrated demand zone, e.g., stadium evacuation can also be modelled using the developed MEDS tool. However, the computation time may vary from a scenario to another.

10.2 Contributions of the Research

The novel contribution of this study includes the development of a mass evacuation decision support (MEDS) tool that is flexible to consider multiple types of disruptions and uncertainties in assessing mass evacuations. The modular-based approach adopted in this study enables the MEDS tool to capture uncertainty and risks associated with a mass evacuation within a traffic evacuation microsimulation model. State-of-the-art modelling methods and techniques are used to develop the modules. The study also leverages the modules to inform a zonal vulnerability assessment. One of the unique features of this research is that it uses zonal vulnerability characteristics to ascertain vulnerability-based prioritization of evacuees when planning for countermeasures. The key contributions of this research include the development of the following modules using the cutting-edge modelling methods and techniques.

1. A major contribution of this research is that it develops a framework for a large-scale traffic evacuation microsimulation model which implements a dynamic traffic assignment (DTA) process. The DTA process captures dynamic traffic congestion propagation and driver's route choices in response to continuously changing traffic conditions in the network. The microsimulation model generates scenario evaluation results at a finer grained detail that can further be utilized by other modules of different functions within the developed evacuation modelling framework.

2. The study further contributes to developing a process mechanism to incorporate evacuation transit network component into the traffic microsimulation model. The study develops optimization models for marshal point location and transit route choice decisions to facilitate a multimodal evacuation scenario analysis and evaluation. The optimization problem is solved using an advanced solution algorithm "Branch and Cut" that generates high-quality solutions in a significantly reduced computation time compared to that of the traditional methods.

3. One of the key features of this study is that it combines a flood risk model, and the traffic evacuation microsimulation model to examine the impacts of flooding related traffic disruptions on the evacuation processes. The flood risk model utilizes a high-resolution LiDAR data and follows a Digital Elevation Modelling (DEM) approach to simulate floods of different water levels over Halifax region. Thus, the research quantifies the natural disaster related impacts on the transportation infrastructures and evacuation traffic flows in the network.

4. This research develops a collision prediction model to add capacity of the MEDS tool to accommodate for further underline uncertainty in

evacuation. The study explores a novel probabilistic approach combining Bayes theory and Monte Carlo simulation technique. Bayes theory involves a probabilistic estimation process which is critical to capture the uncertainty in the occurrence of vehicle collision. This research contributes to identifying influential factors affecting vehicle collision occurrence through a parameter sensitivity analysis. Unlike other studies, it determines the collision hotspots in the light of identified factors rather than using a single given criterion such as traffic volume. The research further advances the traffic microsimulation modelling by incorporating vehicle collision related traffic disruptions for assessing evacuation scenarios.

5. Another key contribution of this study includes that it takes a holistic approach considering geophysical, socioeconomic and mobility challenges to assess zonal vulnerability in the context of a mass evacuation. The study contributes to developing a probabilistic vulnerability assessment model that overcomes the limitation of the traditional models. The vulnerability assessment in this study follows a Bayesian Belief Network (BBN)-based modelling approach. The unique strength of the developed BBN model is that it captures the causal relationship among variables affecting vulnerability. The BBN model utilizes the outputs from a flood risk model, a long-term simulator, and a traffic evacuation microsimulation model. The vulnerability assessment information from the BBN model further informs the countermeasure scenario building process.

6. Finally, the study explores two strategic level countermeasures that simultaneously control a large traffic demand and best utilize the network capacity during an evacuation. One of the unique contributions of this study is that it develops a novel prioritization process following a

fuzzy logic approach for staged evacuation. Furthermore, it fills the gap in literature by considering all modes in evacuation, particularly, transit and school buses through the advanced optimization modelling. The study overcomes the computational challenges with combinatorial optimization by using a dynamic programming for Knapsack optimization.

10.3 Future Research Directions

This study presents the development process of a novel framework for a modular-based mass evacuation decision support (MEDS) tool that assesses evacuation scenarios considering the uncertainty and risks occurrence. Moreover, it also prioritizes evacuees for evacuation based on their priority needs. The results from microsimulation of evacuation scenarios subjected to different disruption risks provide insights into potential low to high level impacts in terms of evacuation times, and traffic congestion. The flood risk model used in this study simulates flooding extent for a single point of time. It does not consider the temporal aspect of flooding which could be useful to determine the timing of evacuation order. Furthermore, the study uses two shelters on the east and north side of the peninsula, respectively. The shelters are highway 102 and highway 118 bound and well spacious to accommodate for the demand used in this research. The use of other shelters may change the traffic flows and congestions in the network. Future study may use shelter location recommendations made by Alam et al. (2021) for the same study area.

The multimodal traffic evacuation microsimulation model facilitates evacuation of transit-dependent population and the results indicate that bus has adaptive capacity to accommodate additional demand, e.g., in a scenario of mode-switching from auto to bus. As this study follows a curb-side simulation approach, evacuation of the residents with mobility issues is not adequately addressed. It would be interesting if a new module is combined with the traffic microsimulation model to calculate the additional time required to move this specific group of residents from an origin location to a curbside. In the case of transit route optimization, a dynamic optimization with consideration of the temporal variation in simulated travel time could provide more insights into evacuation conditions. In addition, a heuristic/meta-heuristic may need to be developed for larger optimization or evacuation problems. One of the important elements of evacuation planning is communication strategy and dissemination of information regrading different aspects of evacuation, for example flooding extent, marshal point locations, bus routes and schedules. Further application of the MEDS tool in future should consider the communication and dissemination strategies in assessing evacuation processes. Particularly, it is important to implement communication and dissemination plans within the simulation model to convey real time information to drivers about the routes for shifting given the accident on route, or large congestion ahead in the network.

The traffic microsimulation modelling of traffic disruptions due to vehicle collision during evacuation provides an upper limit of evacuation time while an evacuation scenario without considering any disruption offers a lower limit of evacuation time in this study. The study did not consider the adjustments in evacuees' departure times in response to collision-related disruptions. An extension of this study should evaluate evacuation scenarios considering the changes in evacuation decisions in response to uncertainty and risks. Moreover, if the collision data observed on an evacuation day is found, it would be interesting to validate the collision prediction model developed in this study.

The countermeasure scenario analysis using MEDS tool offers encouraging results. The developed staged evacuation model incorporates geophysical, social and mobility characteristics in prioritizing areas for evacuation.

However, the study did not track socio-economic characteristics of individuals when simulating traffic movement. In addition, the study did not consider trip chaining problems (e.g., pick-up kids and family members). Further research will be necessary that uses activity-based travel demand models for demand estimation and real-time bus supply assessment within all mode allocation module. In this research, MEDS tool uses information from iTLE. It would be interesting if the tool can be embedded within the iTLE, particularly, as a traffic assignment component. This coupling would enable to develop future evacuation plans using the long-term simulator of iTLE. Short-term simulator can inform the MEDS tool with activity-based travel demand information. MEDS tool can also be leveraged to develop a scenario building module that would enable emergency professionals playing with different scenarios and assist decision making process. It would also be worth to explore how the MEDS framework can be extended to incorporate an epidemiological model representing pandemic, e.g., COVID 19 and determine how the evacuation process would further be complicated. One of the important focus of future research could include collecting data or designing experiment to understand panic behaviour and replicate more planning scenarios within the developed modelling system in this research.

10.4 Concluding Remarks

This study advances the evacuation modelling literature by developing multiple modules that capture different types of uncertainties and risks in assessing evacuation processes within a traffic evacuation microsimulation model. The MEDS tool developed in this study assesses the impacts of natural disaster as well as traffic operation related network disruptions on evacuation process through a coupling mechanism. A novel prioritization method is developed in this research to better represent the vulnerable population and their priority needs within the implementation process of countermeasure, namely staged evacuation. This research also addresses the gap in literature by utilizing all modes in evacuation through a combined optimization and traffic microsimulation modelling approach.

The mass evacuation decision support tool will assist the transportation engineers/planners and management professionals at different levels of government to consider efficient and optimum evacuation strategies. Furthermore, organizations at municipalities and national levels can utilize the tool to evaluate the effectiveness of new infrastructure development for emergency situations. The scenario analysis using the tool will give insights in developing the contingencies and fiscal planning for emergency evacuation

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Appendices

Appendix A Flooding Extents

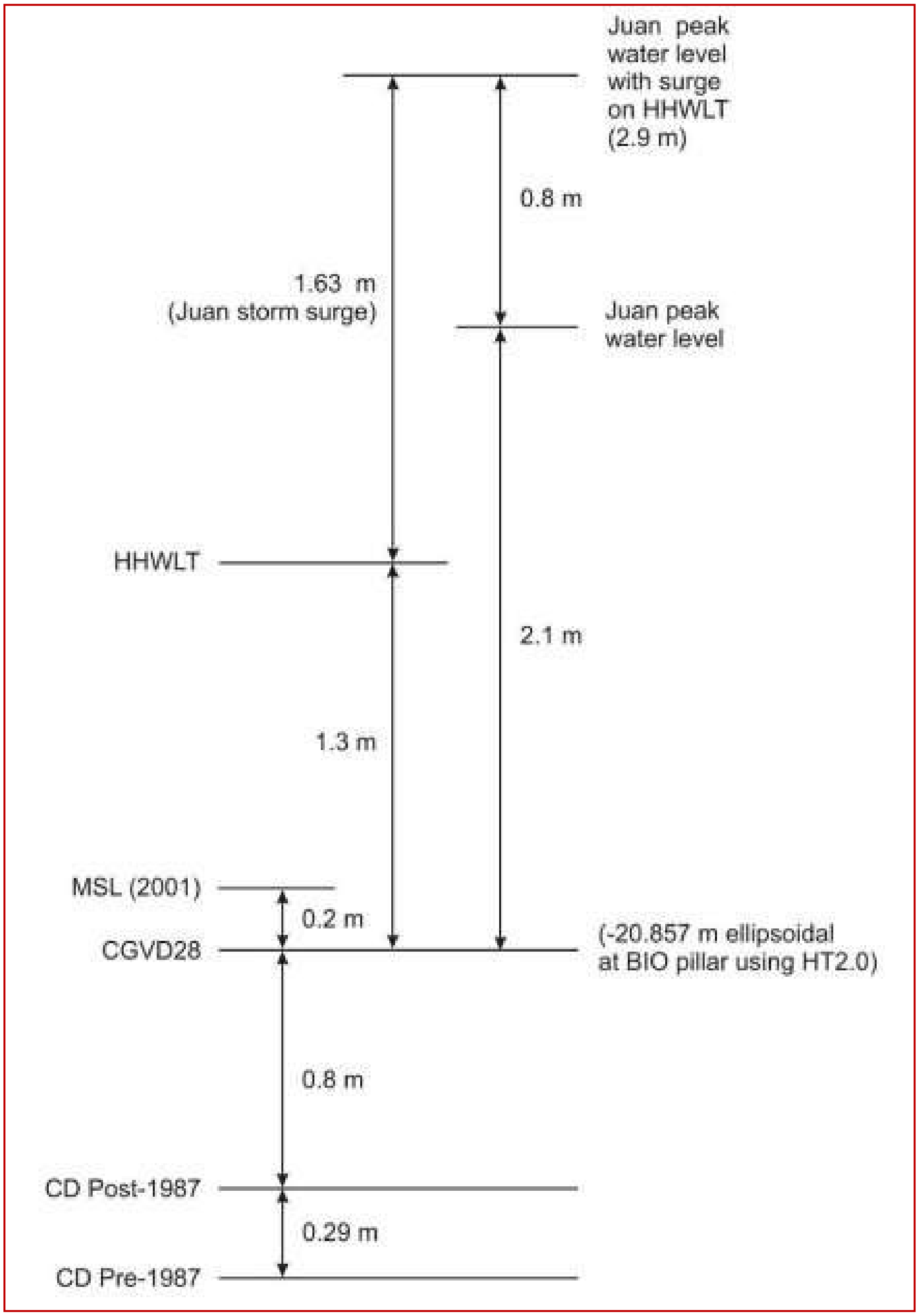

Figure A – 1 Juan's peak water level of 2.1 m CGVD28, had it occurred on HHWLT the water level would have been 2.9 m CGVD28

Figure A – 2 The flooding extent of the Halifax Peninsula under a 15.0 m flooding scenario

Figure A – 3 The flooding extent of the Halifax Peninsula under a 30.0 m flooding scenario

Figure A – 4 The flooded links of the Halifax Peninsula transport network under a 2.9 m flooding scenario

Figure A – 5 The flooded links of the Halifax Peninsula transport network under a 3.9 m flooding scenario

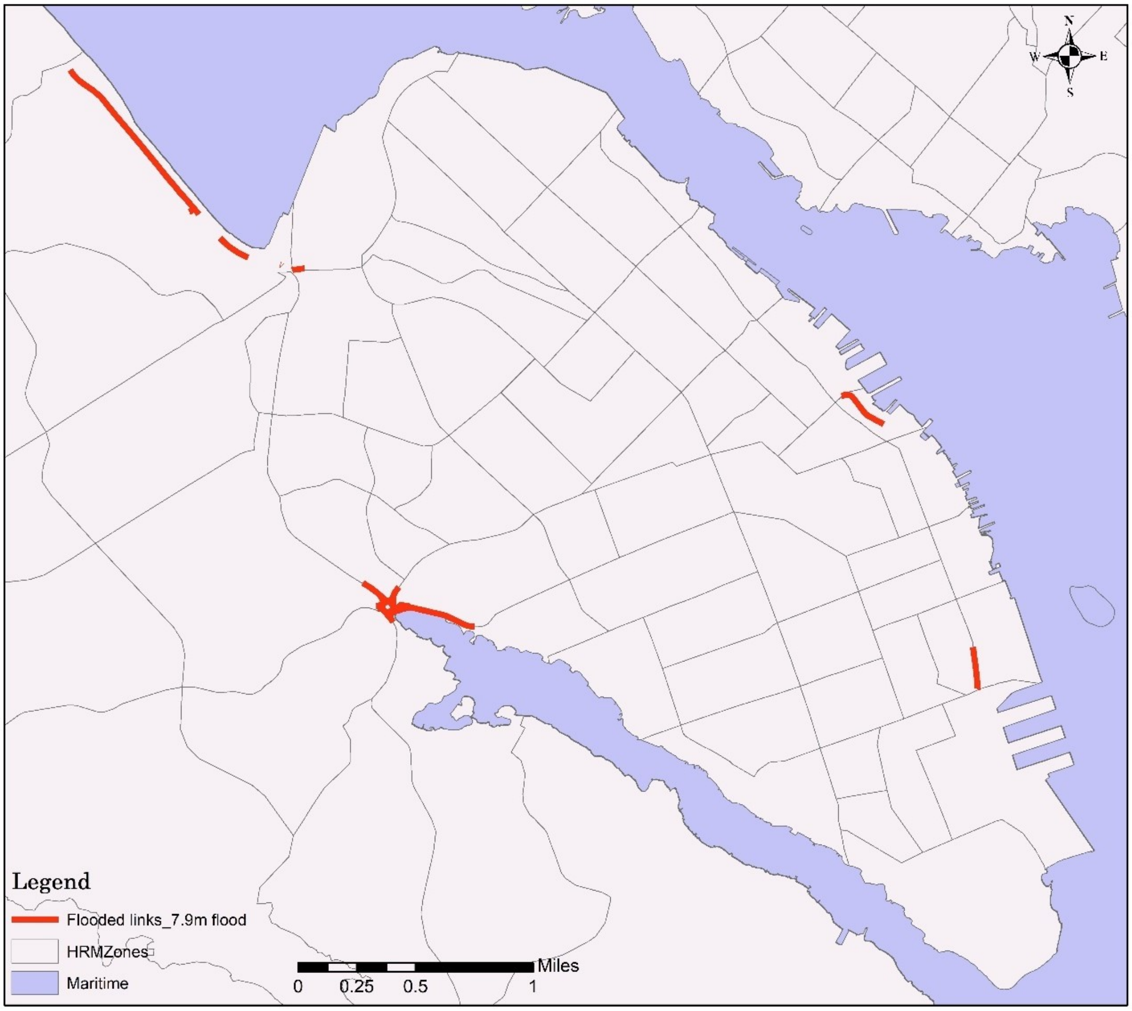

Figure A – 6 The flooded links of the Halifax Peninsula transport network under a 7.9 m flooding scenario

Appendix B Zonal Clearance Times

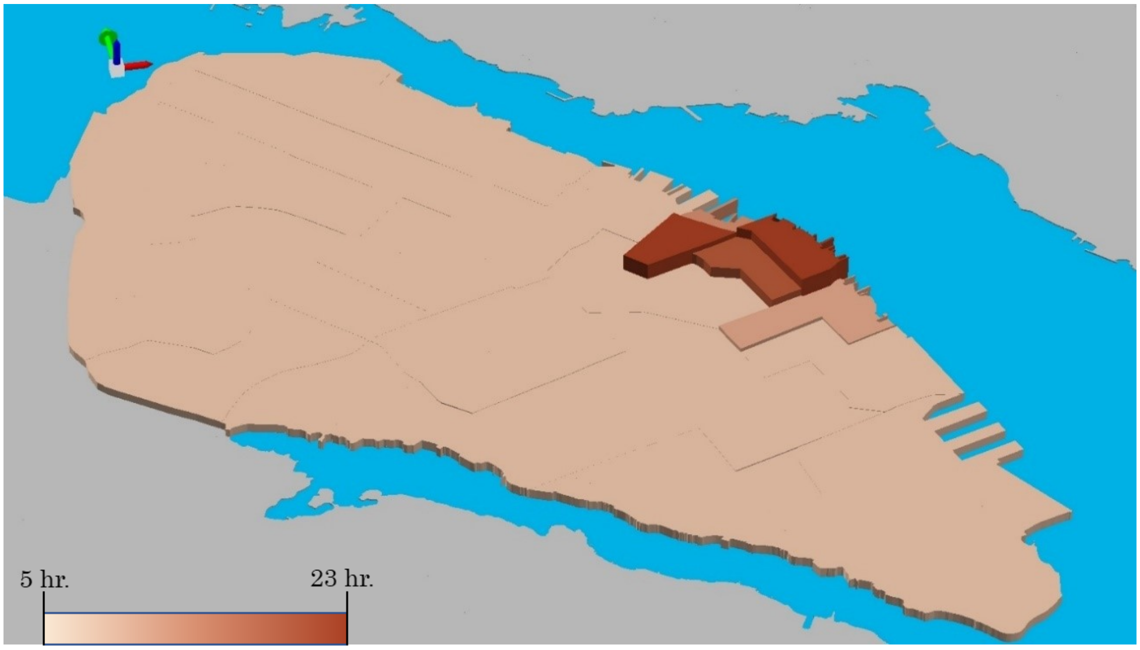

Figure B – 1 A 3-D visualization of clearance time across Halifax Peninsula TAZs when no flood occurs

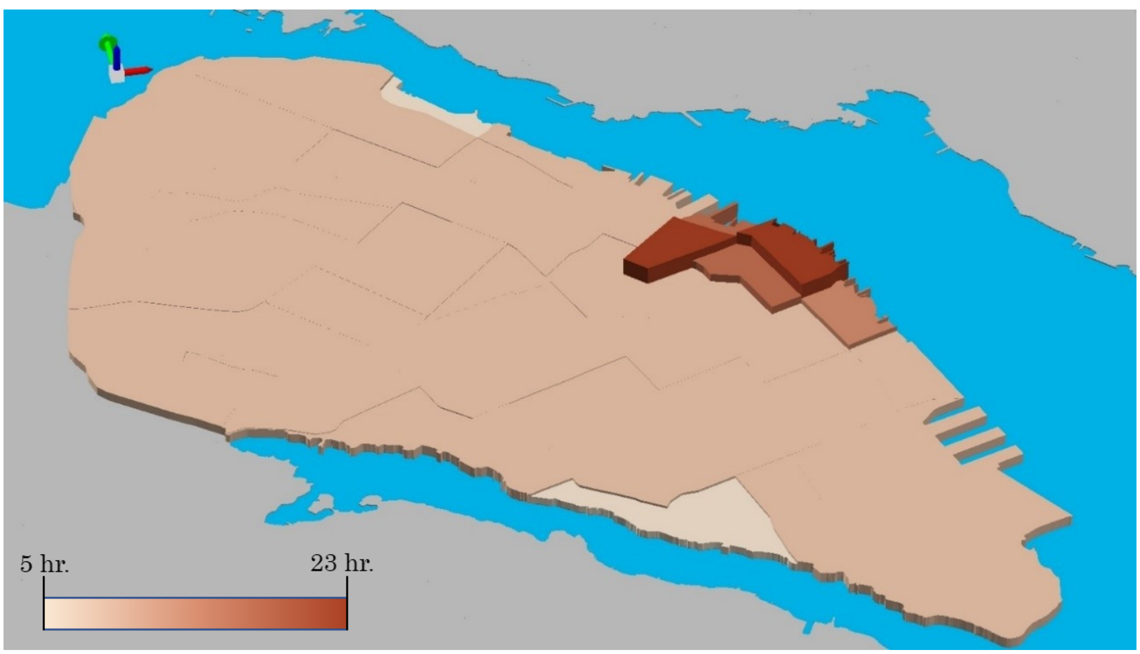

Figure B – 2 A 3-D visualization of clearance time across Halifax Peninsula TAZs under a 2.9 m flooding scenario

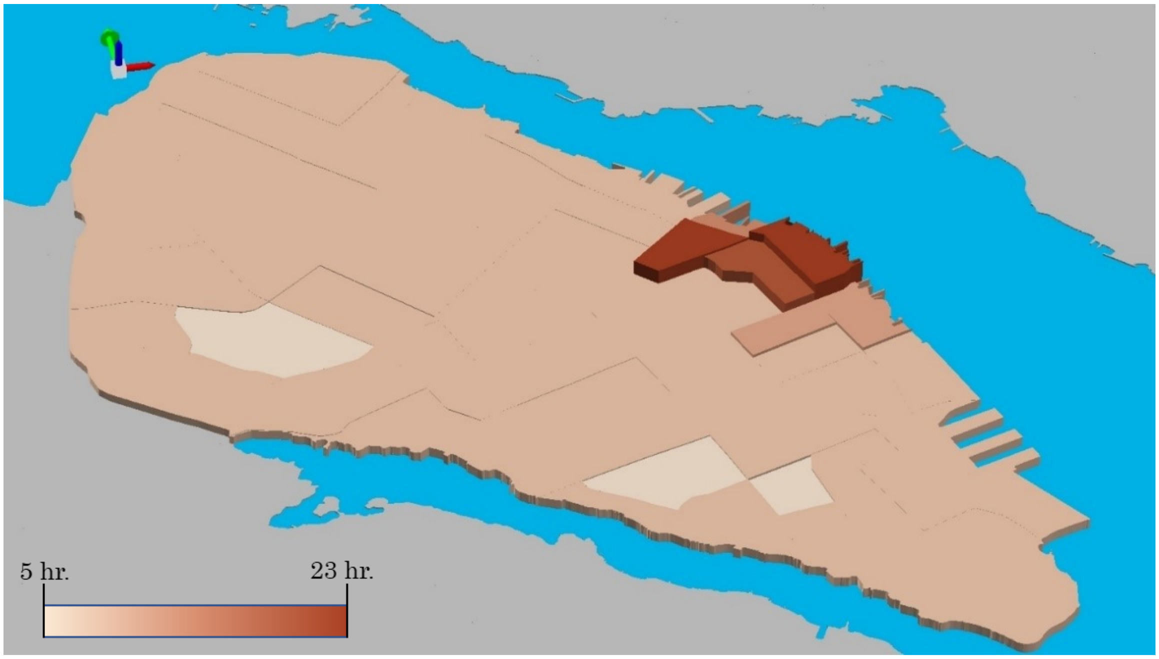

Figure B – 3 A 3-D visualization of clearance time across Halifax Peninsula TAZs under a 3.9 m flooding scenario

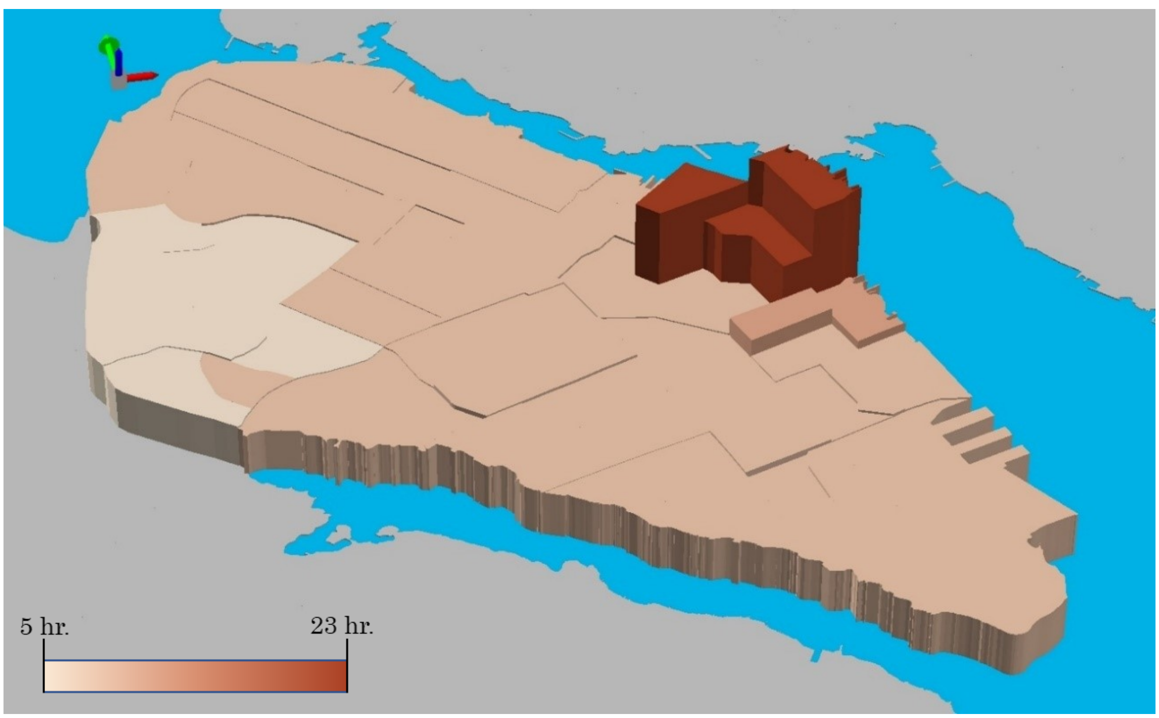

Figure B – 4 A 3-D visualization of clearance time across Halifax Peninsula TAZs under a 7.9 m flooding scenario

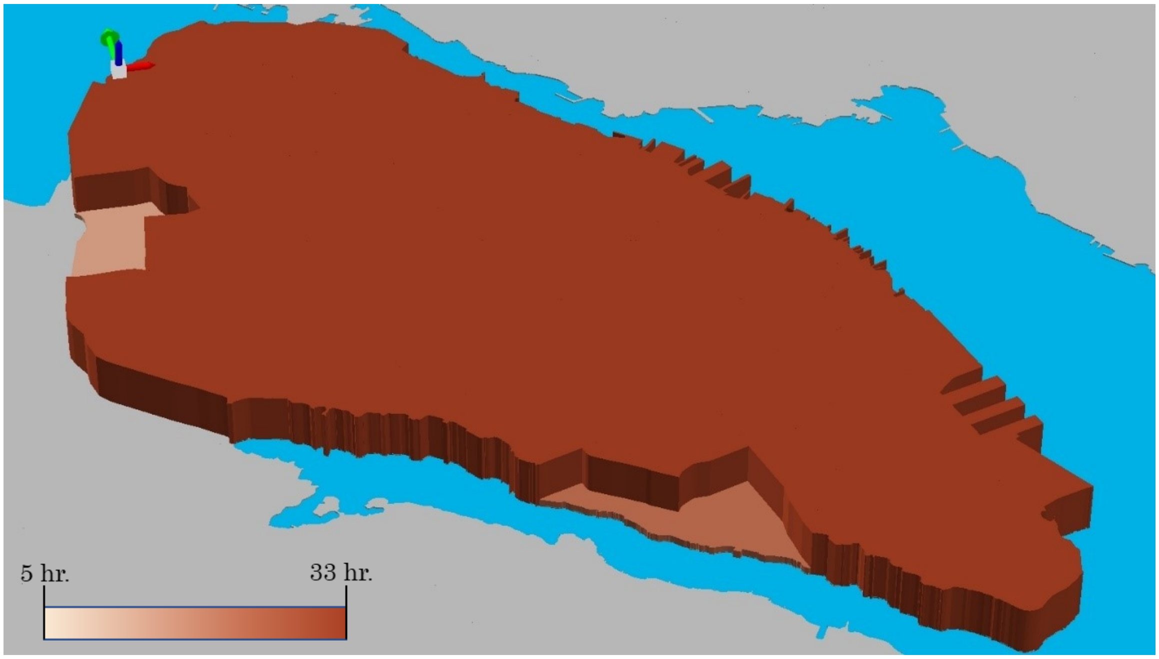

Figure B – 5 A 3-D visualization of clearance time across Halifax Peninsula TAZs under a scenario of vehicle collisions at five critical locations

Figure B – 6 A 3-D visualization of clearance time across Halifax Peninsula TAZs under a staged evacuation scenario

Figure B – 7 A 3-D visualization of clearance time across Halifax Peninsula TAZs when 10% auto-based demand are served by transit and school buses

Figure B – 8 A 3-D visualization of clearance time across Halifax Peninsula TAZs when 15% auto-based demand are served by transit and school buses

Figure B – 9 A 3-D visualization of clearance time across Halifax Peninsula TAZs when 20% auto-based demand are served by transit and school buses

Appendix C Evacuation Traffic Flows and Congestion

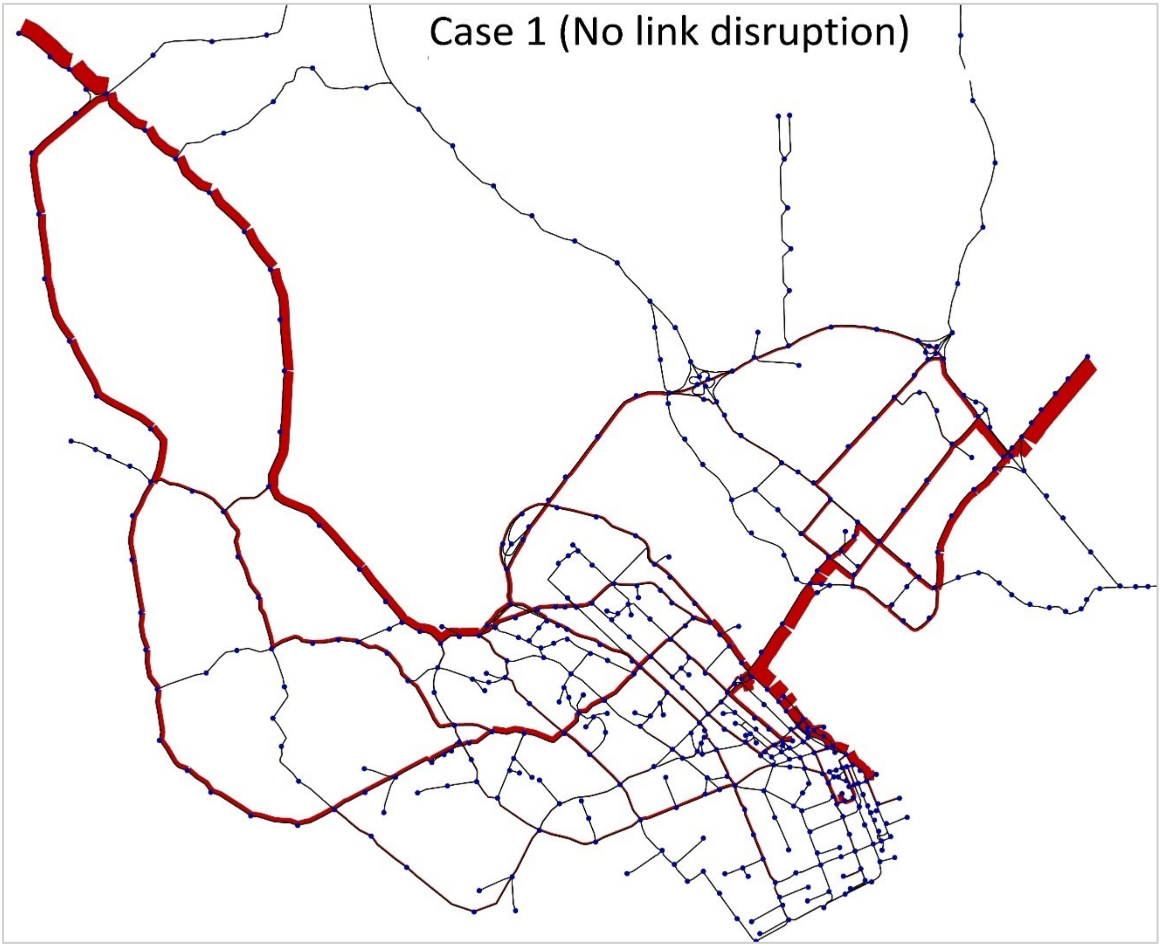

Figure C – 1 Traffic flows in the Halifax transport network when no flooding occurs

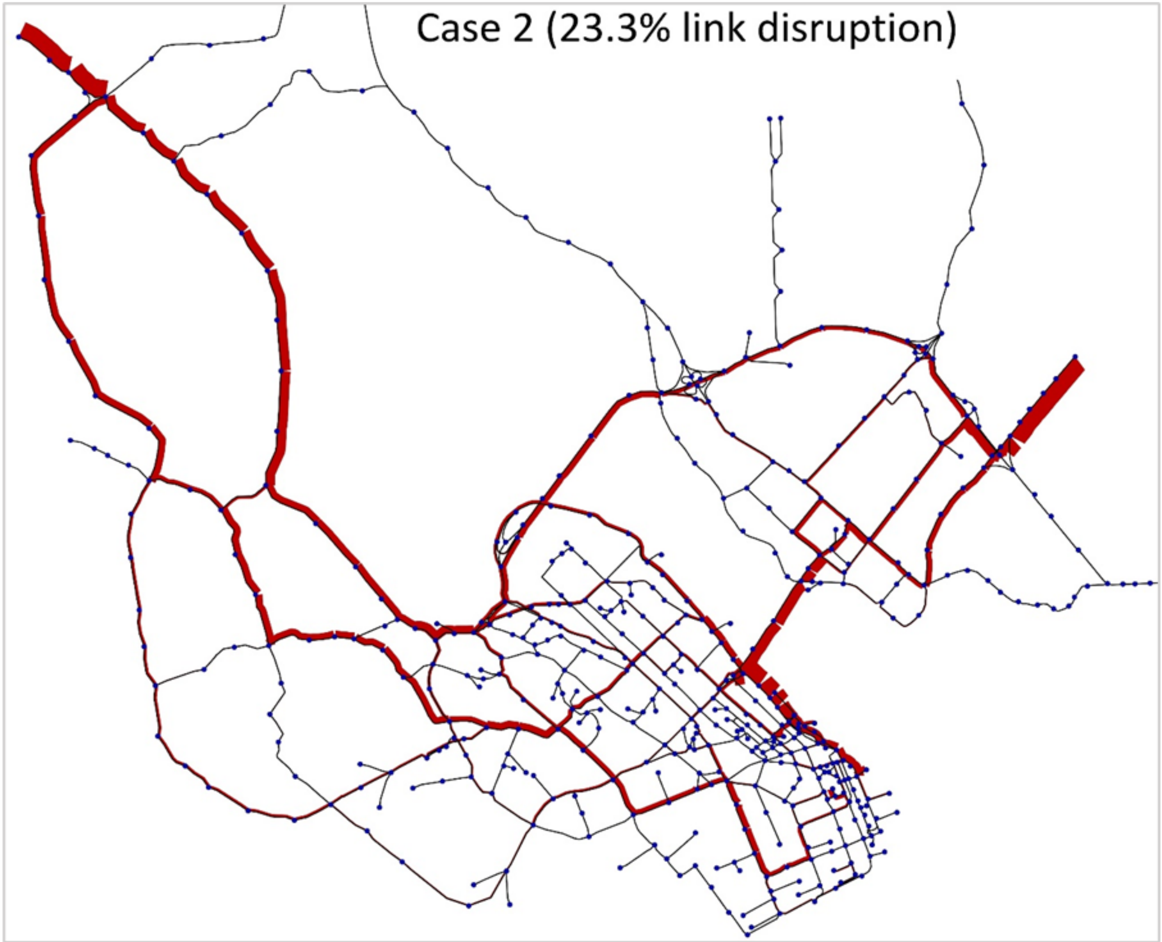

Figure C – 2 Traffic flows in the Halifax transport network under a 2.9 m flooding scenario

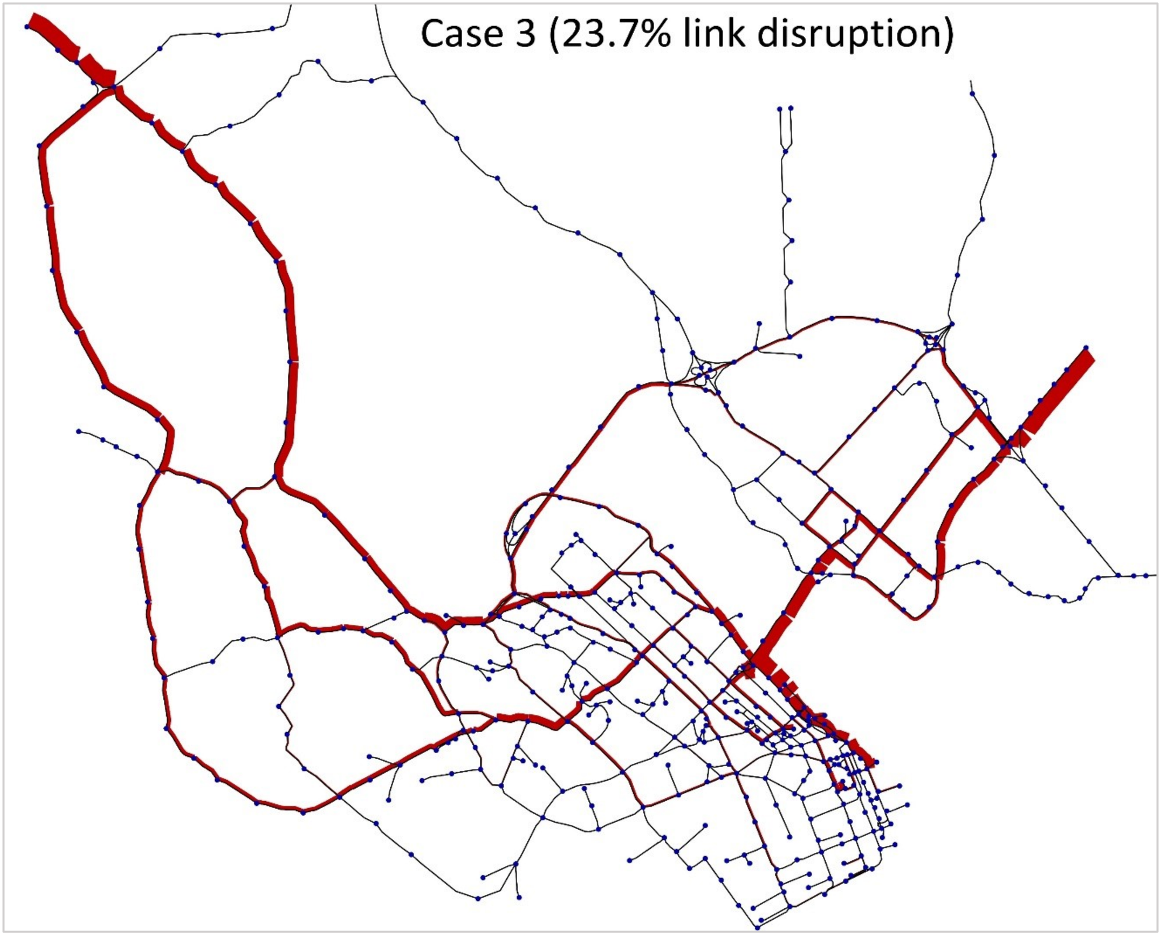

Figure C – 3 Traffic flows in the Halifax transport network under a 3.9 m flooding scenario

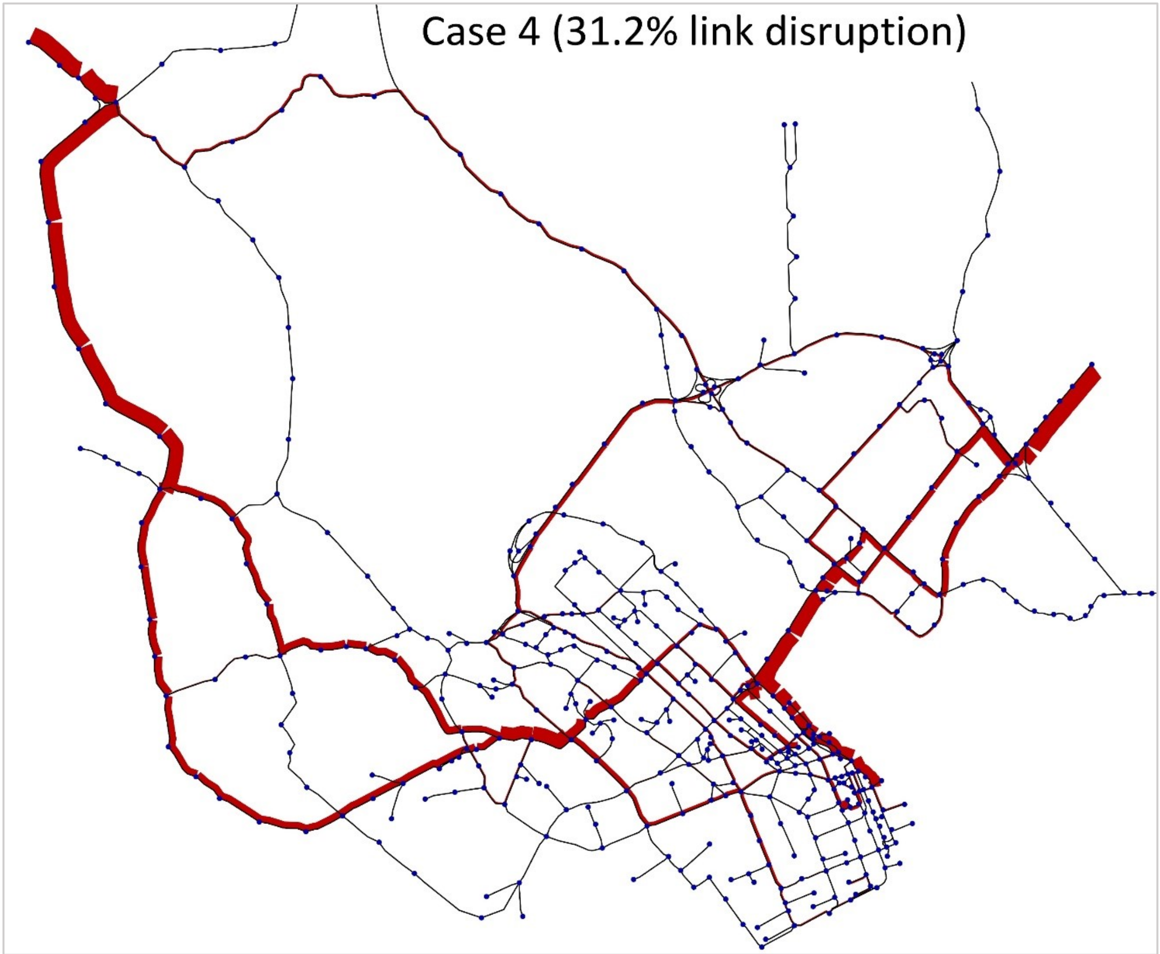

Figure C – 4 Traffic flows in the Halifax transport network under a 7.9 m flooding scenario

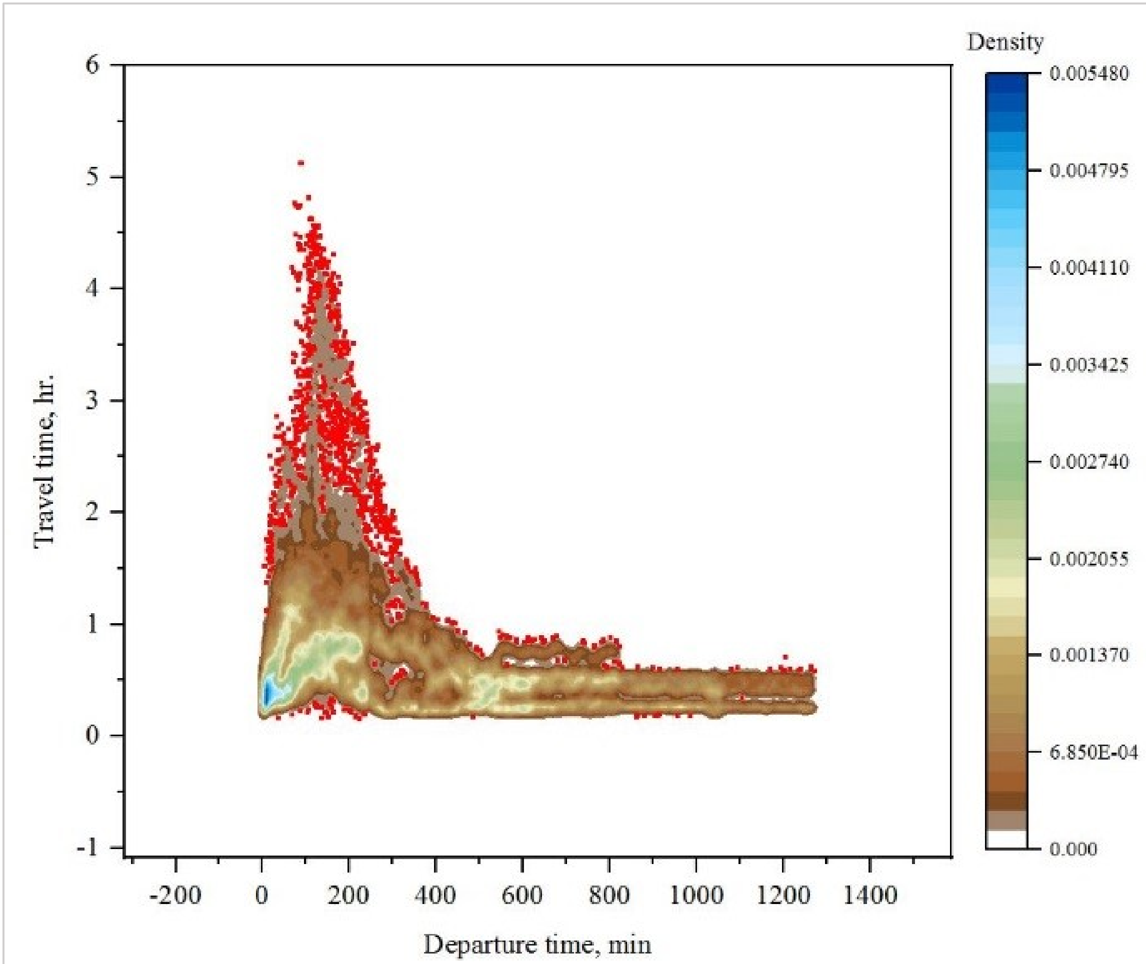

Figure C – 5 Evacuees' travel time in relation to their departure for evacuation when no flooding occurs

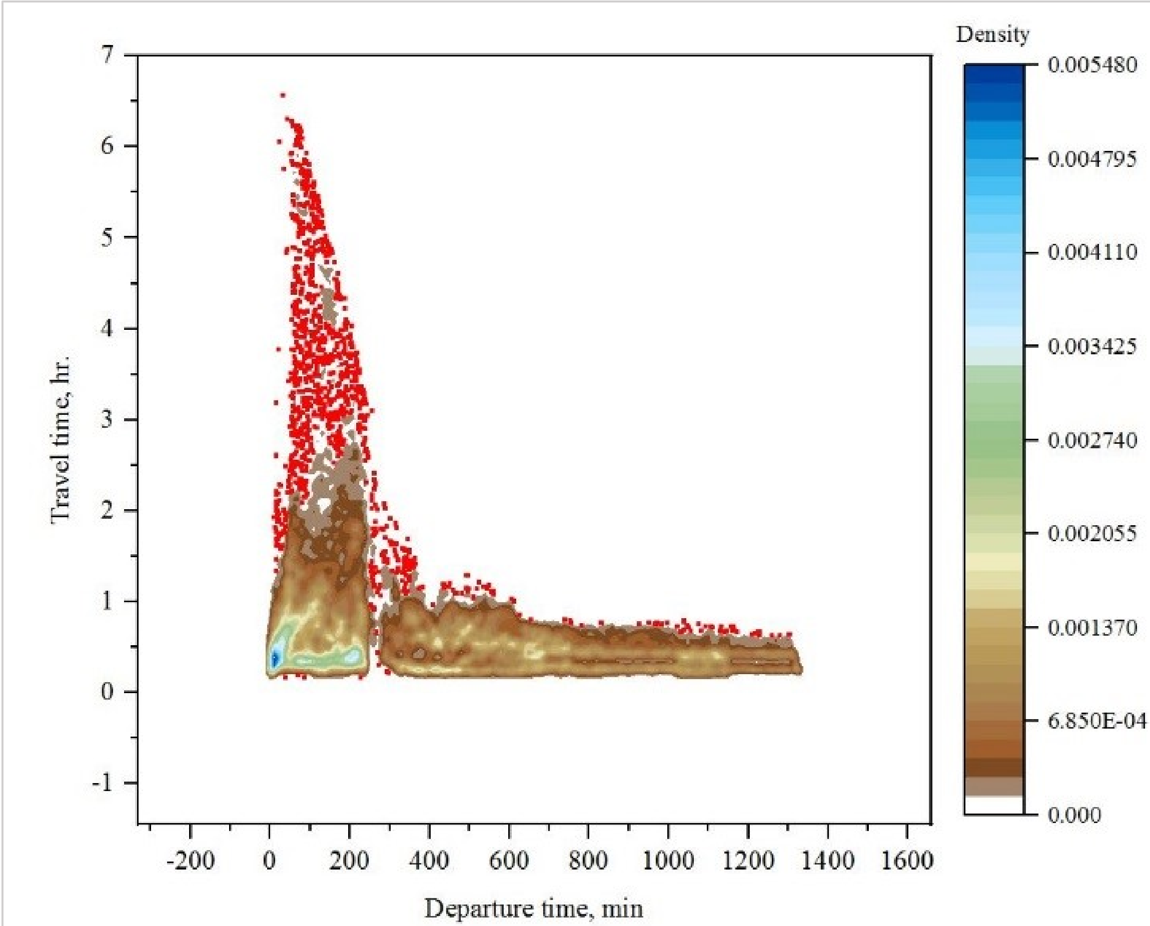

Figure C – 6 Evacuees' travel time in relation to their departure for evacuation under a 2.9 m flooding scenario

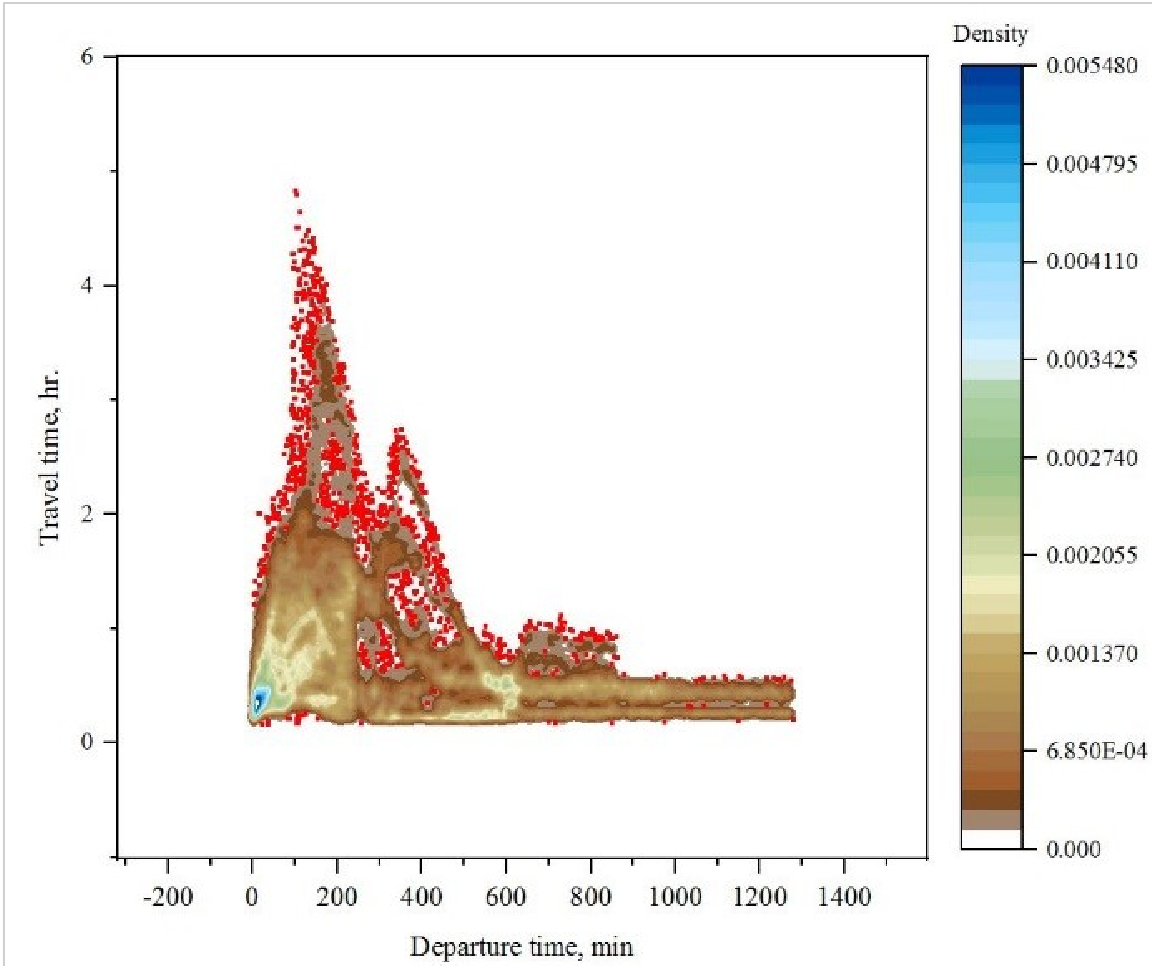

Figure C – 7 Evacuees' travel time in relation to their departure for evacuation under a 3.9 m flooding scenario

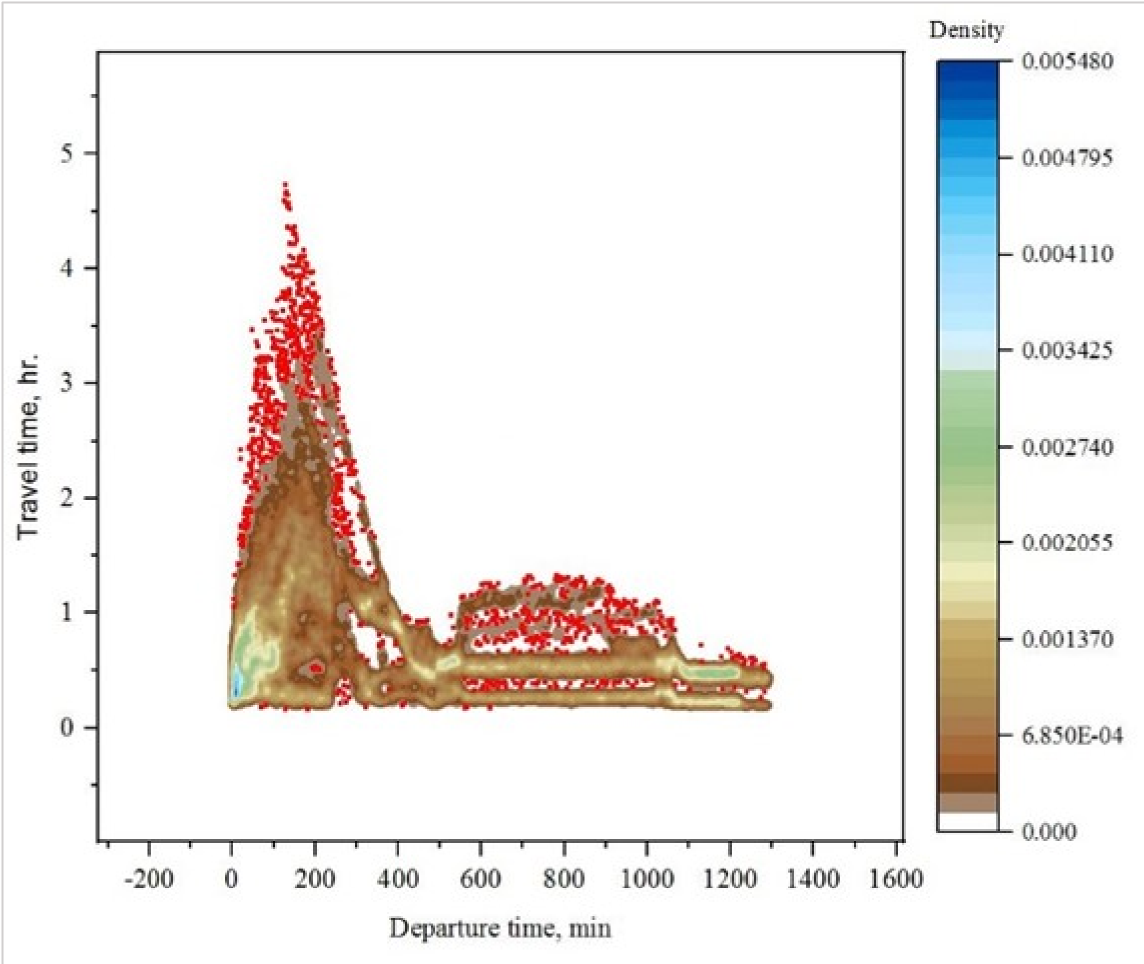

Figure C – 8 Evacuees' travel time in relation to their departure for evacuation under a 7.9 m flooding scenario

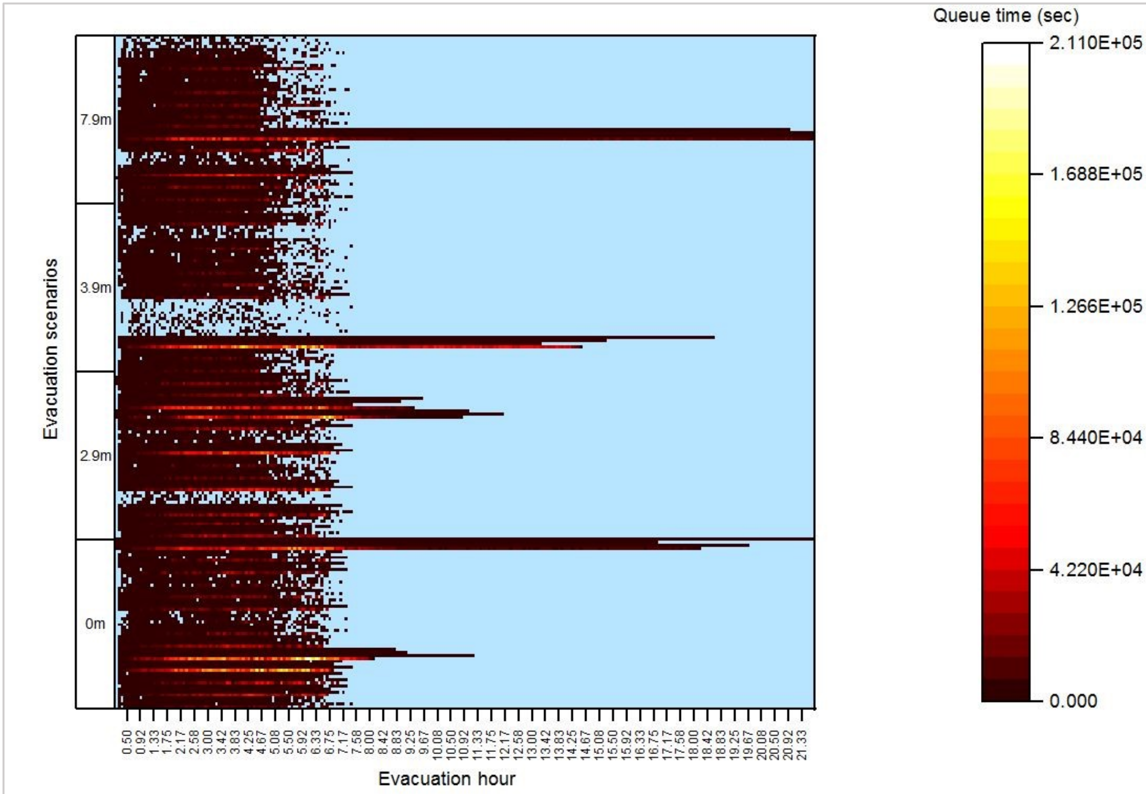

Figure C – 9 Queue time anticipated with the progression of evacuation time under different flooding scenarios (each horizontal line represents a TAZ)

Figure C – 10 Traffic evacuation and congestion visualization within a traffic evacuation microsimulation model

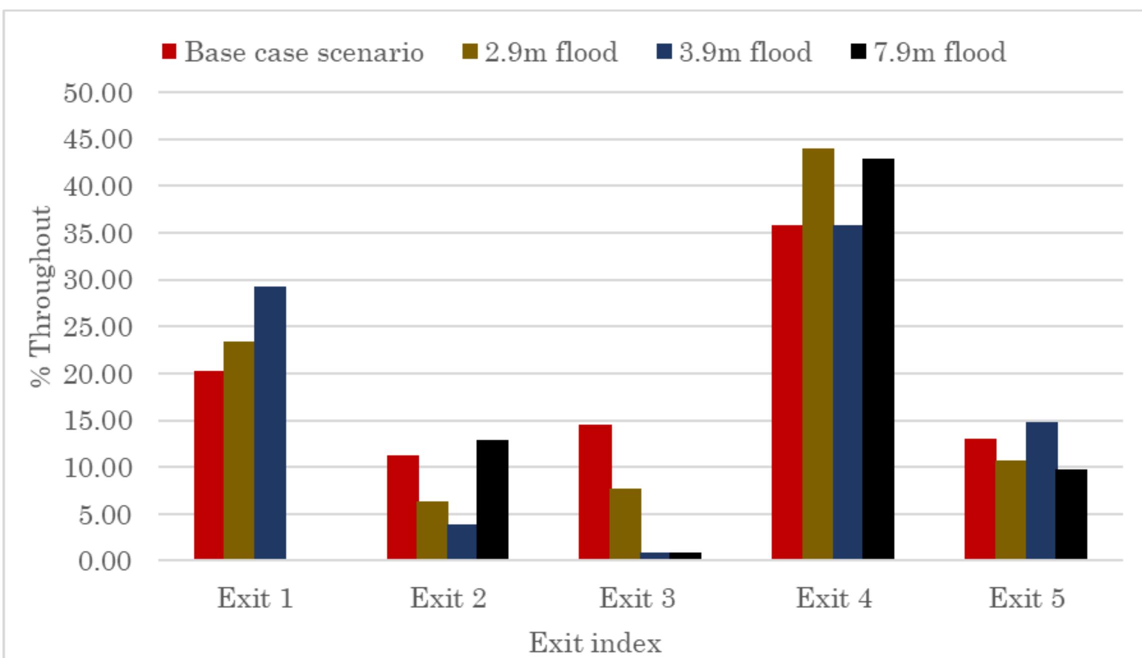

Figure C – 11 Percent accomplished evacuation through different exit points of the Halifax Peninsula

Appendix D Multimodal Evacuation

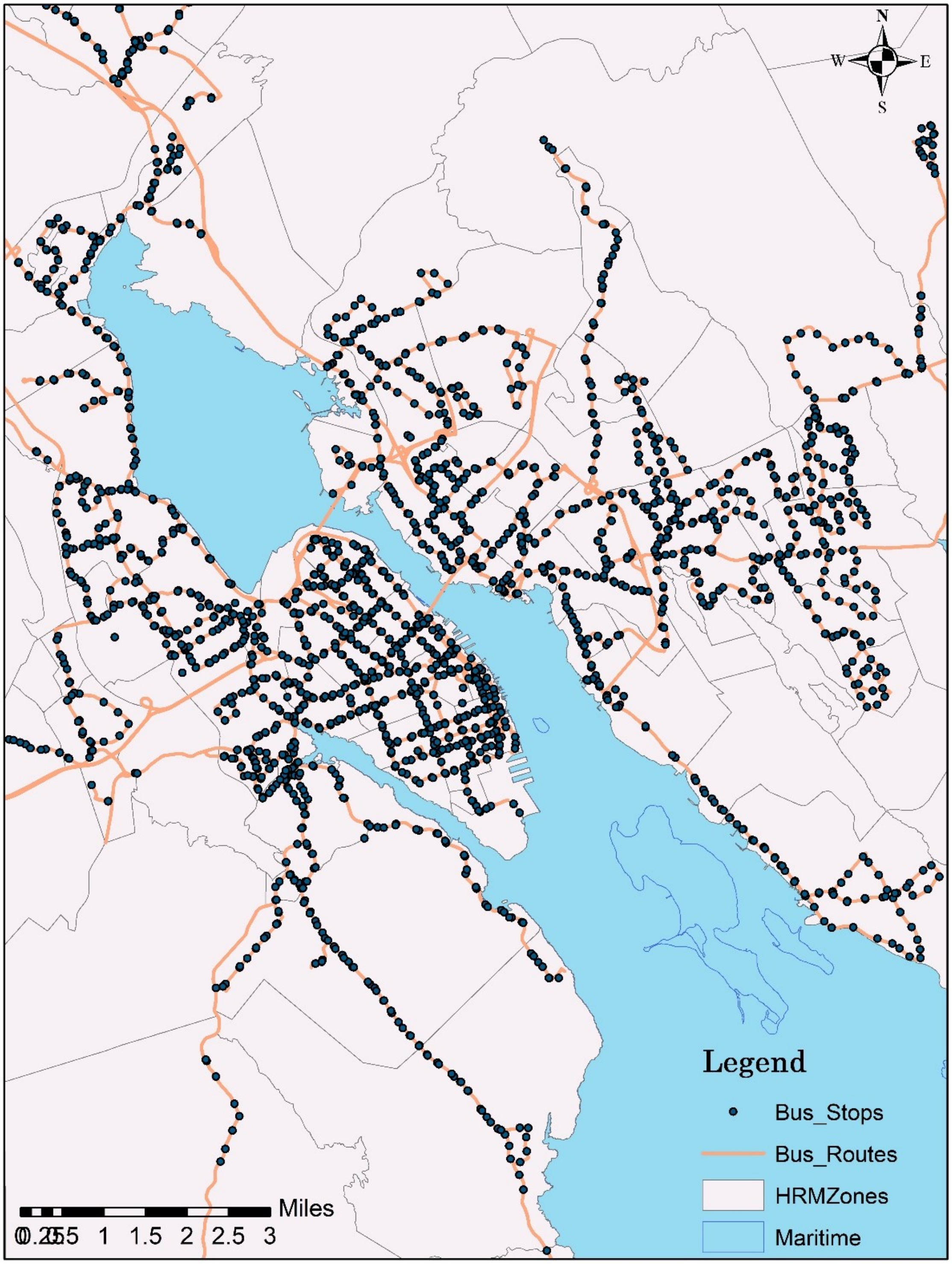

Figure D – 1 Transit lines and bus stops data used for optimizing marshal point locations and evacuation transit lines

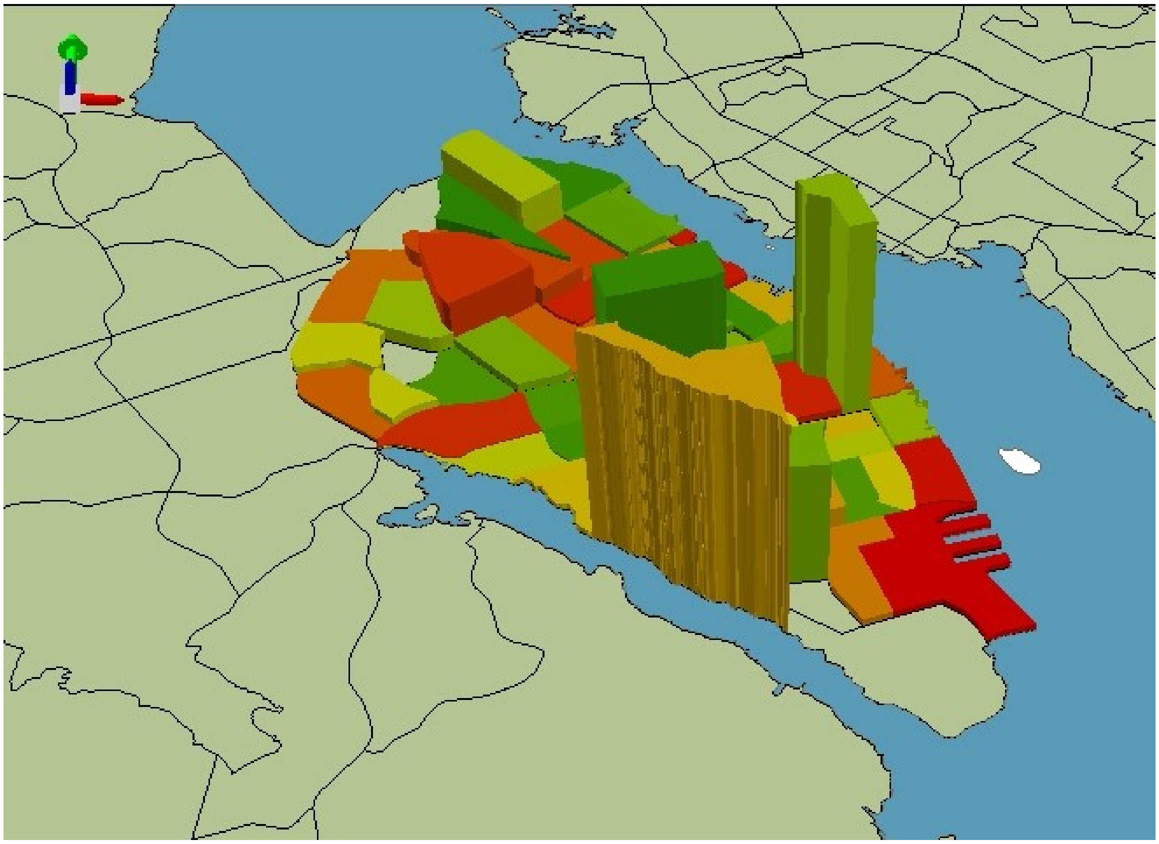

Figure D – 2 Transit demand data obtained from Halifax Network Model and used for optimizing marshal point locations and evacuation transit lines