



A STAGED EVACUATION MODELLING FRAMEWORK

Prepared by:
M.J. Alam and M.A. Habib

Prepared for:
MacEachen Institute for Public Policy and Governance, Dalhousie University

Research Report 2021-01

2021

Dalhousie Transportation Collaboratory (DalTRAC)
Rm B105, Dalhousie University, PO Box: 15000
1360 Barrington Street, Halifax, NS Canada, B3H 4R2

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1. Introduction

This study develops a framework for mass evacuation modeling that considers staged evacuation during a hurricane or a flood. 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. Therefore, pre-evacuation planning without the consideration of vulnerabilities may give a rise to societal and equity issues (Whitefield, 2006). For instance, low mobility 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. 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 conventional evacuation generally associates spontaneous behavior of evacuees and more often overlook the priority needs of the vulnerable population. 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. Staged evacuation is a useful tool that is used to maintain a priority-based entry of evacuation traffic in the network and move the affected people to shelters or other identified safe zones efficiently. However, the process inherently induces ethical dilemmas and raises equity concerns. Therefore, this study develops a staged evacuation modelling framework that accounts for vulnerability characteristics in prioritizing the vulnerable population for 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, while geophysical vulnerability stems from their topographic locations. Moreover, a high traffic demand and a long clearance time refers 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. 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 decide prioritizing 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 modeling that assesses the priority needs of vulnerable populations in relation to their geophysical, social, and mobility characteristics within a traffic microsimulation model. The novelty of this research includes the development of a sequential modeling system that comprises of a fuzzy logic-based modeling 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 modeling or an approximate reasoning mechanism to handle the impacts of subjective information in the 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 (BBN) vulnerability assessment model that provides vulnerability information that considers 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.

2. Literature Review

Evacuation modeling 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 modeling. 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 modeling (Sadri et al., 2015), cell-based network optimization modeling (Liu et al., 2006; Li and Han, 2015), traffic microsimulation and agent-based simulation modeling (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 decided to evacuate. Hence, delays in departure time was 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, 2020) and in the evacuation for Hurricane Rita, people were stuck on the road for 10-12 hours (Blumenthal, 2020). 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 are conducted on staged evacuation. There is a growing interest in studying nature, extents, procedures, and protocols in relation to staged evacuation. **Table 1** lists key studies and contributions in the field of staged evacuation. These studies encompass a wide variety of modeling methods ranging from network flow modeling to agent-based traffic simulation modeling 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. (2012) 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 evaluate 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 modeling approach is necessary to ascertain a vulnerability-based prioritization within staged evacuation modeling.

The proposed framework in this study fills the gap in literature by incorporating a fuzzy logic - based staged evacuation model that ascertain a vulnerability-based prioritization of zones that are 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, 2019b) 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 and subjective 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 modeling framework that addresses different aspects of vulnerabilities to prioritize areas for an evacuation and to predict the impacts of a staged evacuation on a region with different geographical locations and a range of socio-economic characteristics. The study employs a traffic microsimulation model to test and evaluate staged evacuation scenarios obtained from the proposed integral planning and modeling 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 1: Key Studies and Contributions in the Field of Staged Evacuation

| Authors | Methods | Evacuation types | Details/Contributions/Gaps | Findings |
|---------------------------------|---|------------------------------------|--|---|
| Chien and KoriKanthimath (2007) | Analytical modeling | 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. (2012) | 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 et al. (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 modeling | 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 modeling | 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 modeling | 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 travel time with moderate improvement for inland zones. |

| Authors | Methods | Evacuation types | Details/Contributions/Gaps | Findings |
|-------------------------------|---|------------------------------------|--|--|
| Mitchell and Radwan (2006) | Traffic simulation modeling | 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 modeling 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 mode. For the ring road, there is no benefit of using staged evacuation. |
| Chen (2008) | Traffic microsimulation modeling | 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. |

3. Methodology

The sequential evacuation modeling 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) development of a 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.

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. 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 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. Details regarding vulnerability information can be found in Alam and Habib (2019b). 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 1.

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

Zone A

Zone B



| | |
|---|---|
| <p>Zone A</p> <p>Zonal Social Vulnerability: LOW</p>  <p>Zone to Shelter Clearance Time: 12.5</p> <p>--</p> | <p>Zone B</p> <p>Zonal Social Vulnerability: MEDIUM</p>  <p>Zone to Shelter Clearance Time: 5.0 Hours</p> |
|---|---|

Figure 1 A sample card from the prioritization exercise

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 2**. 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.

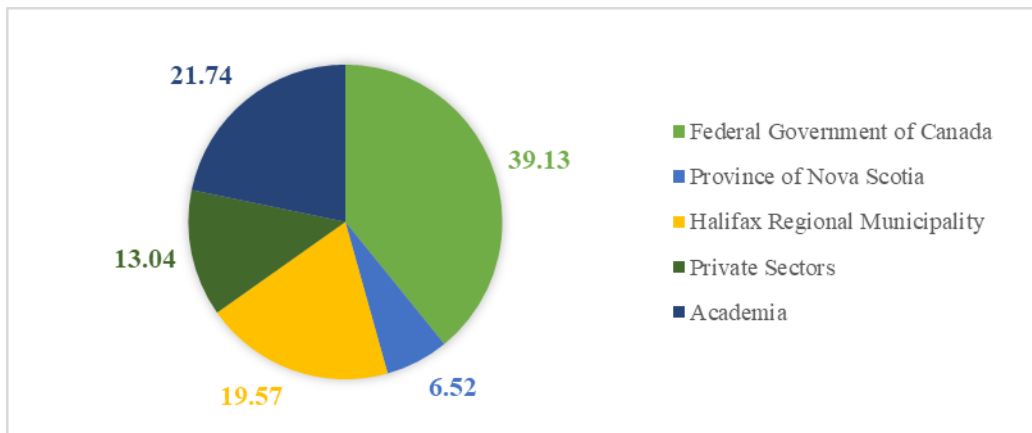


Figure 2 Stakeholder categories by percentage

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.

3.2. Fuzzy Logic - based Approach for Prioritization Weights

The vulnerabilities of traffic analysis zones and the prioritization by experts obtained from the workshop is subjective in nature that it involves imprecise and non-numerical information. Therefore, this study adopts a fuzzy logic approach to analyze the qualitative response by 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-based 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 et al., 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:

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

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.

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 2** linguistic terms and numerical elements for all the input and output variables.

Table 2: Elements of Linguistic Variable 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 |

This information from **Table 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 3**. Next, linguistic variables obtained from the fuzzification stage are used for making fuzzy inferences.

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 the corresponding membership values for a max. – min. composition method used in this stage. The output from fuzzy inference further informs defuzzification process in the next phase.

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, 2011) in the defuzzification stage. The expression used to derive the crisp output value ψ^* is shown below:

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

Where, ψ^* is the crisp value, which continuously changes with the change in input values.

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 based on certain fuzzy rules and (3) defuzzification that computes crisp values for prioritization weights. As shown earlier in **Table 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 2**, the following input-output fuzzy sets are developed in **Figure 3**.

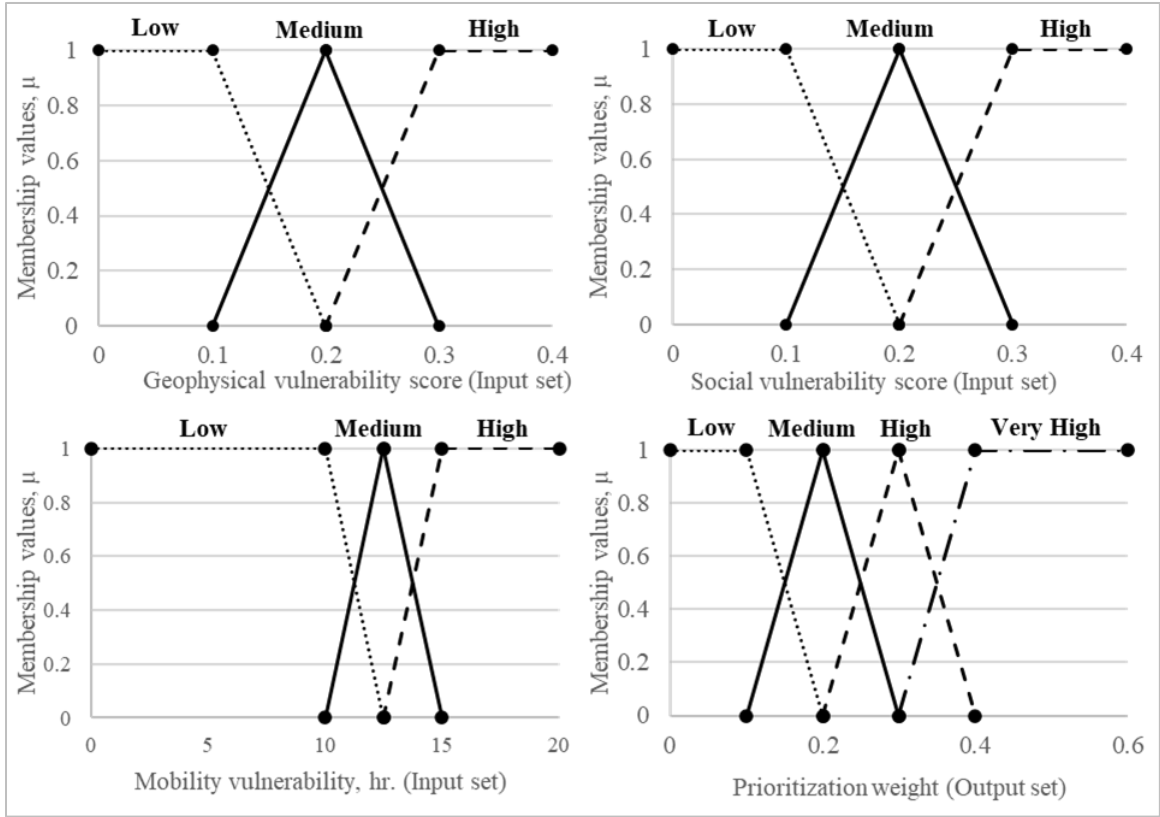


Figure 3: Fuzzy sets for input and output variables

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 membership functions shown in **Figure 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 3**. The final fuzzy inference output i.e., membership values are utilized in the next phase ‘Defuzzification’ to obtain the crisp value representing prioritization weight of the intended zone. A sample calculation is shown in **Table 3** for the demonstration of fuzzification, and the max-min composition method used in

fuzzy inference stage. Furthermore, **Figure 4** shows the defuzzification process used to convert the fuzzy inference output to a crisp value.

Table 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 |

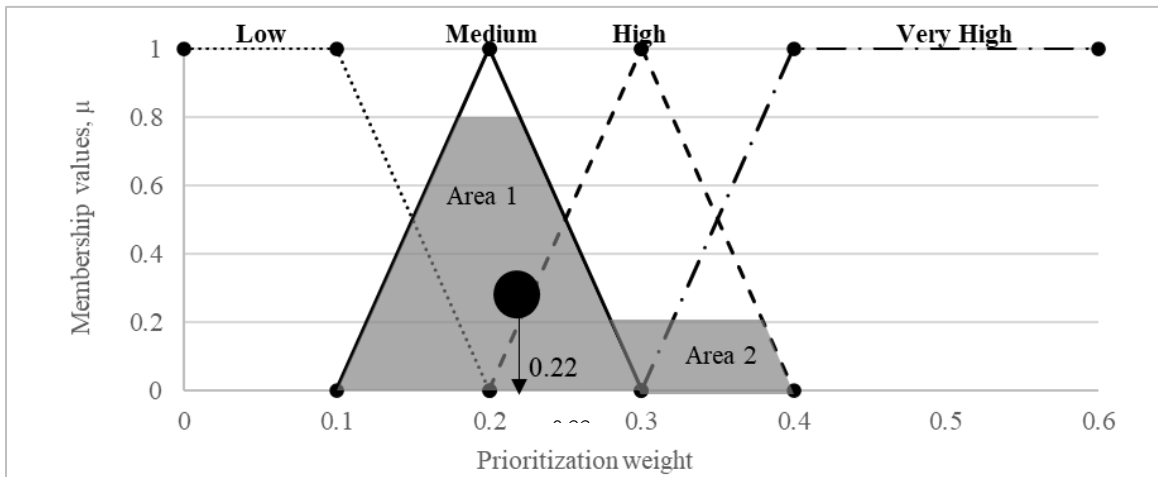


Figure 4: Defuzzification for prioritization weights of traffic analysis zones

The crisp value of 0.22 obtained through defuzzification represents the centroid of the shaded region in **Figure 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 3**. This study identifies four planning districts comprised of traffic analysis zones within Halifax 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.

5. Traffic Evacuation Microsimulation Modeling 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 (using an auto occupancy rate of 1.6 obtained from a Nova Scotia Travel Activity Survey) 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.

6. Results and Discussions

6.1. Prioritization Weights of TAZs for Staged Evacuation

For the analytical and staged evacuation process, all TAZs were divided into four planning districts such as 'Downtown (DT)', 'West-End (WE)', 'North-End (NE)', and 'South-End (SE)' (**Figure 5**). **Table 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 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 people use transit for their evacuation. 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.

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).

6.3. Overall Network Performance for Staged Evacuation

This study examines overall network performance for a staged evacuation in Halifax. **Figure 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 6**). The overall network performance results in **Table 5** suggest that the average delays and the total distance traveled 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 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 7**, the box plot shows relatively a taller upper whisker indicating a greater chance for these zones to anticipate higher queue times.

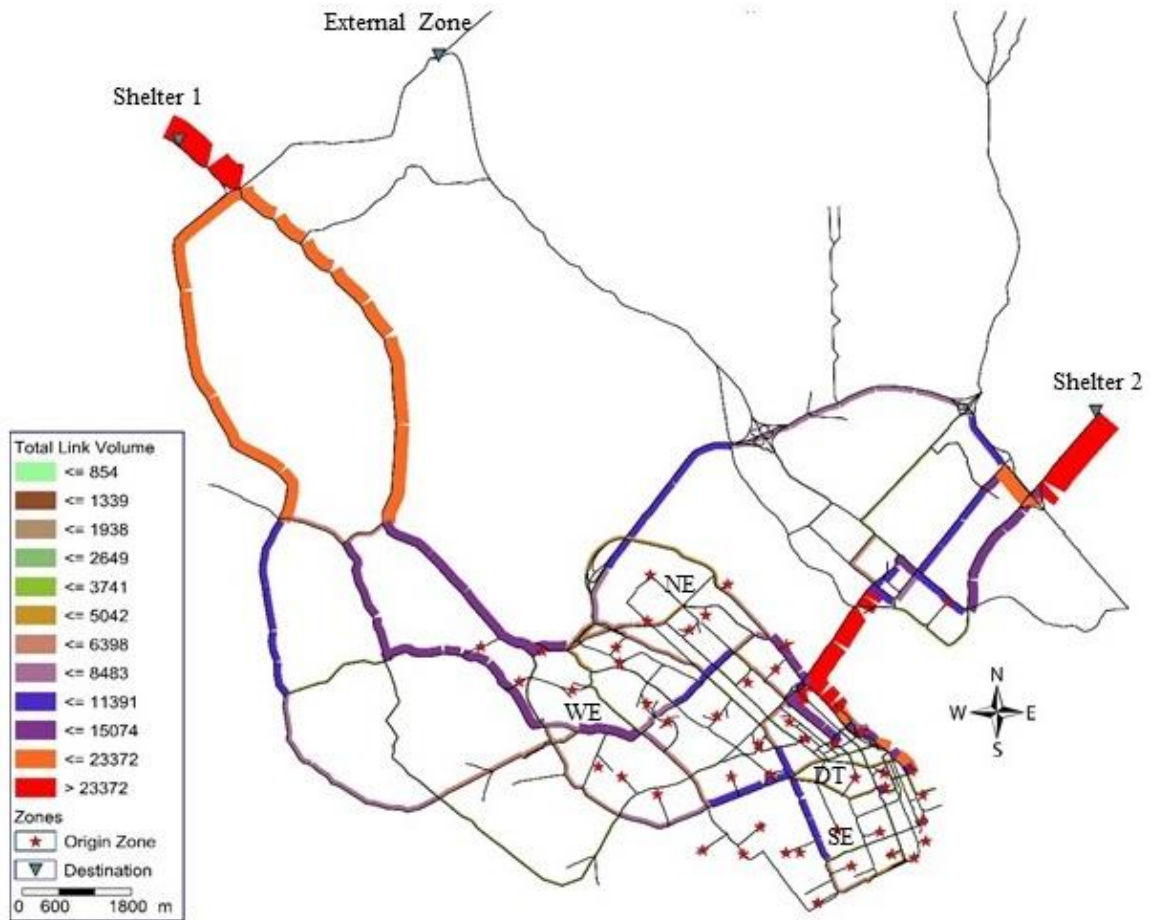


Figure 5: Origins, shelter locations, and traffic flow visualization in the network

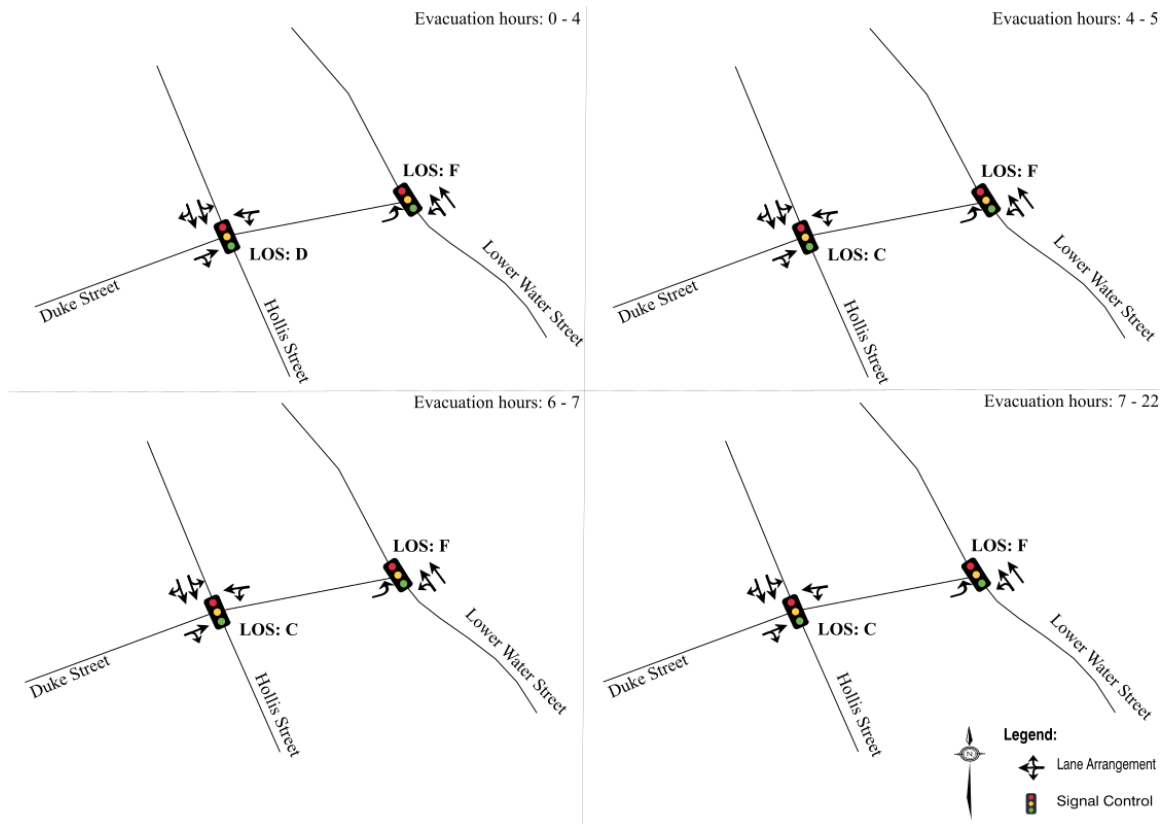


Figure 6: Level of Service (LOS) at intersections ‘Lower Water St at Duke St’ and ‘Hollis St at Duke St’ for a staged evacuation of Halifax Peninsula

The reason is that evacuees **from** these zones travel across the city to arrive at a distant shelter. Figure 6 also shows that Downtown traffic congestion is consistent as the box width is minimal.

Table 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 |

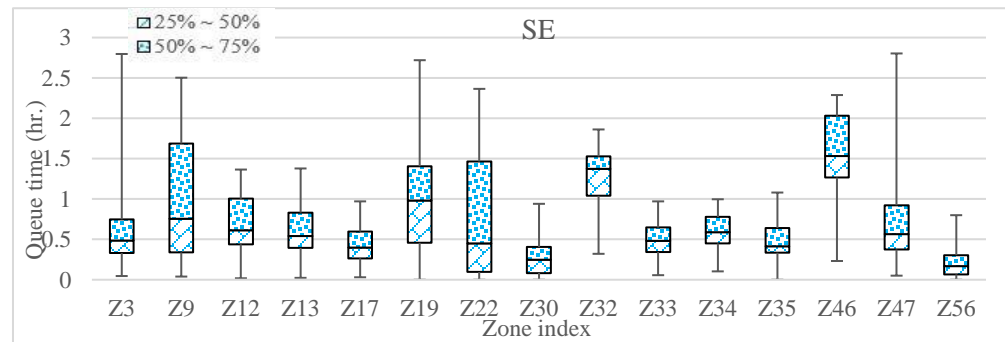
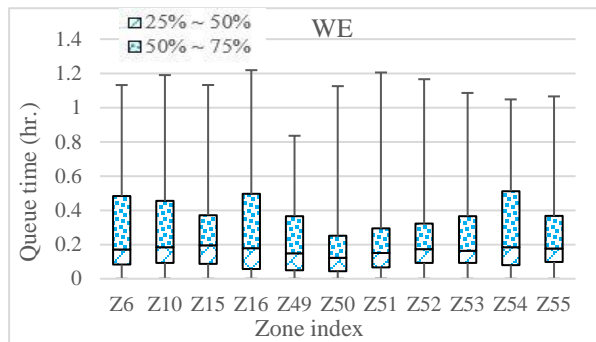
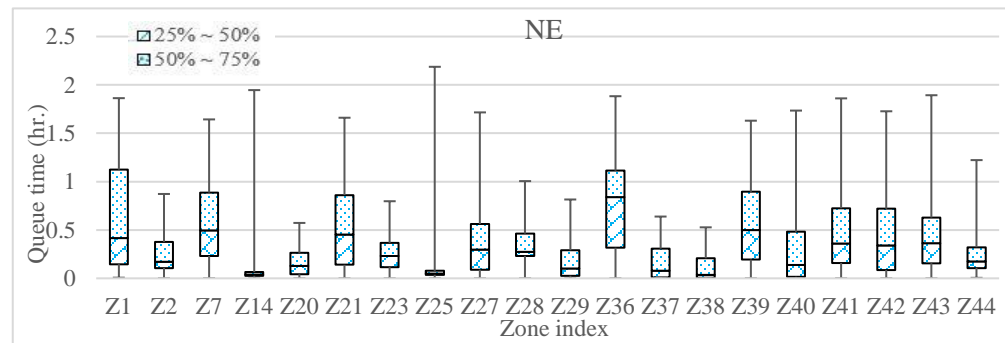
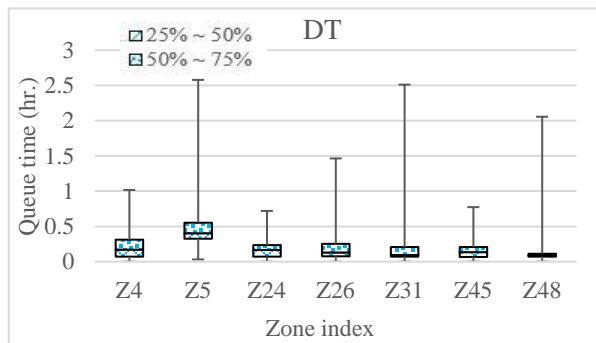


Figure 7: Queue time experienced by traffic analysis zones within four planning districts

6.4. A Comparison of Simultaneous and Staged Evacuation

6.4.1. Traffic Flow Attribute Analysis

Table 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 traveled 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.

6.4.2. Clearance Time Analysis

This study examines evacuation performance across planning districts and traffic analysis zonal levels. **Table 7** presents the total clearance time for each planning district in both simultaneous and staged evacuation scenarios. 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 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 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 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 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 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 |

7. Conclusion

This study presented a fuzzy logic-based staged evacuation modeling framework within 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 modeling system that utilizes a fuzzy logic-based modeling 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 staged evacuation modeling in this study involved the prioritization of planning districts based on their geophysical, social, and mobility vulnerability. The prioritization of 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 operational efficiency for DT. This warrants special plans which may include a transit-based evacuation and traffic operation improvement strategies (e.g., specific evacuation routes) to be integrated within staged evacuation planning. Moreover, the results of this study can be the basis of a zonal prioritization map that can be conveyed to all residents through mobile app or the

EMO website while the map will remain valid for a planning horizon or until any change made to the prioritization process. 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.

REFERENCES

1. Whitefield, P. Left Behind: The Dilemma of Transit for The Disabled and The Poor in a Disaster. Presented at 47th Annual Transportation Research Forum, New York, 2006
2. Chen, X., and F. B. Zhan. Agent-Based Modelling and Simulation of Urban Evacuation: Relative Effectiveness of Simultaneous and Staged Evacuation Strategies. *Journal of the Operational Research Society*, 2008. 59(1): 25-33
3. Zhang, Z., K. Spansel and B. Wolshon. Effect of Phased Evacuations in Megaregion Highway Networks. *Transportation Research Record: Journal of the Transportation Research Board*, 2014. 2459(1): 101-109
4. Hsu, Y. T. and S. Peeta. Risk-Based Spatial Zone Determination Problem for Stage-Based Evacuation Operations. *Transportation Research Part C: Emerging Technologies*, 2014. 41: 73–89
5. Ukkusuri, S. V., Hasan, S., Luong, B., Doan, K., Zhan, X., Murray-Tuite, P., and Yin, W. A-RESCUE: An Agent based regional evacuation simulator coupled with user enriched behavior. *Networks and Spatial Economics*, 2017. 17(1): 197-223.
6. Gehlot, H., Zhan, X., Qian, X., Thompson, C., Kulkarni, M., and Ukkusuri, S. V. A-RESCUE 2.0: A High-Fidelity, Parallel, Agent-Based Evacuation Simulator. *Journal of Computing in Civil Engineering*, 2019. 33(2): 04018059.
7. Sadri, A. M.S. V. Ukkusuri, P. Murray-Tuite, and H. Gladwin. Hurricane evacuation route choice of major bridges in Miami Beach, Florida. *Transportation Research Record*, 2015. 2532(1): 164-173
8. Liu, Y., X. Lai, and G. L. Chang. Cell-Based Network Optimization Model for Staged Evacuation Planning Under Emergencies. *Transportation Research Record: Journal of the Transportation Research Board*, 2006. 1964(1): 127-135
9. Li, D. and B. Han. Behavioral Effect on Pedestrian Evacuation Simulation Using Cellular Automata. *Safety Science*, 2015. 80: 41-55

10. Naghawi, H., and B. Wolshon. Performance of Multi-Modal Evacuation Traffic Networks: A Simulation-Based Assessment. Presented at 90th Annual Meeting of the Transportation Research Board, Washington, D.C., 2011
11. Church, R. L. and R. M. Sexton. *Technical Report 3021: Modeling small area evacuation: Can existing transportation infrastructure impede public safety?* Department of Transportation, University of California, California. 2002.
<http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=277BB409D1127FC14265485F3E0DF135?doi=10.1.1.7.2473&rep=rep1&type=pdf>. [Accessed October 23, 2017]
12. Zou, N., S. T. Yeh, G. L. Chang, A. Marquess and M. Zezeski. Simulation-based Emergency Evacuation System for Ocean City, Maryland, during Hurricanes. *Transportation Research Record: Journal of the Transportation Research Board*, 2005. 1922: 138-148
13. Li, X., B. Huang, Z. Liu, X. Zhang and J. Sun. A Novel Method for Planning a Staged Evacuation. *Journal of Systems Science and Complexity*, 2012. 25(6): 1093-1107
14. Alam, M. J. and M. A. Habib. Mass Evacuation of Halifax, Canada: A Dynamic Traffic Microsimulation Modeling Approach. *Procedia Computer Science*, 2019a. 151: 535-542
15. Alam, M. J., M. A. Habib, K. Quigley, K. and T. L. Webster. Evaluation of the Traffic Impacts of Mass Evacuation of Halifax: Flood Risk and Dynamic Traffic Microsimulation Modeling. *Transportation Research Record: Journal of the Transportation Research Board*, 2018. 2672(1): 148-160
16. Wang, H., A. Mostafizi, L. A. Cramer, D. Cox and H. Park. An Agent-Based Model of a Multimodal Near-Field Tsunami Evacuation: Decision-Making and Life Safety. *Transportation Research Part C: Emerging Technologies*, 2016. 64: 86-100
17. Sadri, A. M., S. V. Ukkusuri, and P. Murray-Tuite. A random parameter ordered probit model to understand the mobilization time during hurricane evacuation. *Transportation Research Part C: Emerging Technologies*, 2013. 32: 21-30
18. Sadri, A. M., S.V. Ukkusuri, and H. Gladwin. Modeling joint evacuation decisions in social networks: The case of Hurricane Sandy. *Journal of choice modelling*, 2017. 25: 50-60
19. Lindell, M. K., Sorensen, J. H., Baker, E. J., and Lehman, W. P. Community response to hurricane threat: estimates of household evacuation preparation time distributions. *Transportation research part D: transport and environment*, 2020. 85:102457
20. Lindell, M. K., and Perry, R. W. The protective action decision model: theoretical modifications and additional evidence. *Risk Analysis: An International Journal*, 2012. 32(4):616-632

21. Lindell, M. K., Murray-Tuite, P., Wolshon, B., and Baker, E. J. Large-scale evacuation: the analysis, modeling, and management of emergency relocation from hazardous areas. CRC Press, 2018
22. Marshall, A. How to Move a Million People Out of a Hurricane's Way. Wired, 2018. <https://www.wired.com/2016/10/move-2-million-people-hurricane-matthews-way/> [Accessed in August 20, 2020]
23. Blumenthal, R. Miles of Traffic as Texans Heed Order to Leave. The New York Times, 2005. <https://www.nytimes.com/2005/09/23/us/nationalspecial/miles-of-traffic-as-texans-heed-order-to-leave.html> [Accessed in August 15, 2020]
24. Urbina, E. A. *A State-Of-The-Practice Review of Hurricane Evacuation Plans and Policies*. Master's Thesis, Louisiana State University, 2002.
25. Malone, S. W., C. A. Miller and D. B. Neill. Traffic Flow Models and The Evacuation Problem. *Journal of Undergraduate Mathematics and Its Applications*, 2001. 22(3): 1-47
26. Chen, X. Microsimulation of Hurricane Evacuation Strategies of Galveston Island. *The Professional Geographer*, 2008. 60(2): 160-173
27. Wood, N. J., C. G. Burton, and S. L. Cutter. Community Variations in Social Vulnerability to Cascadia-Related Tsunamis in the US Pacific Northwest. *Natural Hazards*, 2010. 52(2): 369-389
28. Balica, S. F., N. G. Wright and F. van der Meulen. A Flood Vulnerability Index for Coastal Cities and Its Use in Assessing Climate Change Impacts. *Natural Hazards*, 2012. 64(1): 73-105
29. Fuchs, S., C. Kuhlicke and V. Meyer. Editorial for the special issue: vulnerability to natural hazards-the challenge of integration. *Natural Hazards*, 2011. 58(2): 609-619
30. Alam, M. J. and M. A. Habib. Vulnerability Assessment during Mass Evacuation: Integrated Microsimulation-Based Evacuation Modeling Approach. *Transportation Research Record: Journal of the Transportation Research Board*, 2019b, 0361198119848409
31. Zadeh, L. A. Fuzzy Sets. *Information and Control*, 1965. 8(3): 338-353
32. Ridwan, M. Fuzzy Preference-Based Traffic Assignment Problem. *Transportation Research Part C: Emerging Technologies*, 2004. 12(3-4): 209-233
33. Chien, S. I., and V. V. Korikanthimath. Analysis and Modeling of Simultaneous and Staged Emergency Evacuations. *Journal of Transportation Engineering*, 2007. 133(3): 190-197
34. Li, X., Q. Li, and C. Claramunt. A Time-Extended Network Model for Staged Evacuation Planning. *Safety Science*, 2018. 108: 225-236
35. Chiu, Y. C., H. Zheng, J. A. Villalobos, W. Peacock and R. Henk, R. Evaluating Regional Contra-Flow and Phased Evacuation Strategies for Texas Using A Large-Scale Dynamic Traffic

Simulation and Assignment Approach. *Journal of Homeland Security and Emergency Management*, 2008. 5(1).

36. Mitchell, S. W., and E. Radwan. Heuristic Priority Ranking of Emergency Evacuation Staging to Reduce Clearance Time. *Transportation Research Record: Journal of the Transportation Research Board*, 2006. 1964(1): 219-228
37. Sbayti, H., and H. S. Mahmassani. Optimal Scheduling of Evacuation Operations. *Transportation Research Record: Journal of the Transportation Research Board*, 2006. 1964(1): 238-246
38. Bish, D. R., H. D. Sherali and A. G. Hobeika. Optimal Evacuation Planning Using Staging and Routing. *Journal of the Operational Research Society*, 2014. 65(1): 124-140
39. Hawas, Y.E. An Integrated Simulation-Based Fuzzy Logic Model for Real-Time Traffic Signal Control. *Transportmetrica*, 2011. 7(4): 247-278
40. Ali, O. A. M., A. Y. Ali, and B. S. Sumait. Comparison between the effects of different types of membership functions on fuzzy logic controller performance. *International Journal*, 2015. 76: 76-83
41. Gholamy, A., O. Kosheleva, and V. Kreinovich. Why Triangular and Trapezoid Membership Functions Are Efficient in Design Applications. https://scholarworks.utep.edu/cs_techrep/1272/ [Accessed in May 2020]
42. Kikuchi, S., and D. Miljkovic. Use of Fuzzy Inference for Modeling Prediction of Transit Ridership at Individual Stops. *Transportation Research Record: Journal of the Transportation Research Board*, 2011. 1774(1): 25-35
43. Bela, P. L., and M. A. Habib. Urban Freight Network and Emission Modeling for Port City Halifax, Canada: A Spatial and Temporal Evaluation of Commercial Vehicles Movement. Presented at 97th Annual Meeting of the Transportation Research Board, Washington, D.C., 2018
44. Prouse, V., J. L. Grant, H. Ramos and M. Radice. *Assessing Neighborhood Change: Gentrification and Suburban Decline in A Mid-sized City*. Technical Report, School of Planning, Dalhousie University, 2015
45. Silver, J. Public Housing Risks and Alternatives: Uniacke Square in North End Halifax, Canadian Centre For Policy Alternatives–Nova Scotia. Technical Report, Canadian Center for Policy Alternatives. <https://www.policyalternatives.ca/publications/reports> [accessed April 2019]