# COUNTERMEASURE FOR A MASS EVACUATION: A BUS-BASED EVACUATION MODELLING FRAMEWORK

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## 1. Introduction

Natural and human-made disasters have become an ever-present risk, and several extreme natural disasters and large-scale evacuations in recent years highlight the vulnerability of cities to the impacts of the extreme disasters. 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. Countermeasure in the context of a mass evacuation intends to efficiently manage evacuation traffic demand and improve traffic operations in the network. Previous studies revealed that only auto-based evacuation may take a longer time to evacuate a city and/or lead to an incomplete evacuation. For example, the mass evacuation that resulted from Hurricane Florence in 2018 caused hundreds of thousands of people to use 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). Alam et al. (2019) found that it takes 22 hours to evacuate 65,000 evacuees by auto from the Halifax Peninsula, which is alarming and warrants a more efficient evacuation system. Lessons learned from the past evacuations assert that if there needs to be a large-scale evacuation within a short timeframe, all modes of transportation available within the network should play a role in evacuating people from the affected area in an efficient manner. However, most of the existing evacuation plans across North America rarely address the role of all modes in the evacuation plan due to the complexity of developing legislation, arranging coordination among agencies of interests, and the associated liabilities. Existing studies identified the over-arching problem with the use of buses in evacuation, which is the lack of suitable emergency response and evacuation plans that can adequately explain the role of transit and school buses in evacuation (TRB, 2008; Clark and Habib, 2010; Hess and Gotham, 2007). For example, although an evacuation plan is in place for Halifax, Canada, bus-based evacuation is not explicitly identified (Clark and Habib, 2010). A national survey of hurricane evacuation revealed that low mobility and special needs groups are underrepresented in evacuation plans (Wolshon et al., 2001). Specifically, the challenges with the use of buses in evacuation include the identification of vulnerable populations, coordination among stakeholders, marshal point location identification, resource identification and allocations, shelter arrangements with an assurance of food, water, medical care, and security (Cavusoglu et al., 2013; Litman, 2006). It is also vital to train human resources, including drivers for government-assisted evacuation planning. The challenge with arranging training is that transit agencies are reluctant to such sessions as they do not have enough staff to backfill the positions (Renne et al., 2008). This study aims to ensure that all modes available in Halifax, such as cars, public transit, and school buses are adequately evaluated in evacuation plans and are utilized during evacuation operations. The associated challenge is that there is an ethical dilemma in how to allocate the resources. Allocating buses for transit-dependent populations has been in practice since Hurricane Katrina in 2005; however, optimizing an evacuation operation using all modes has not been adequately explored. For example, optimizing the allocation of buses to individuals based on their urgencies is very often overlooked. There will be two types of riders during an evacuation: choice-based transit riders and captive transit riders. Based on our previous research (Alam et al., 2019; Alam and Habib, 2020; Alam and Habib, 2021), the evacuation of the auto and captive transit users from the Halifax Peninsula takes 22-33 hours. On the other hand, during Hurricane Harvey 2017 in Houston, there was no evacuation order as it was thought that evacuating within the short amount of time available was logistically impossible (Wang et al., 2017). Therefore, the interplay between network demand and supply must be optimized to obtain a successful composition of auto-bus mix in the network to ensure that (i) the entire population is evacuated, (ii) the mode-specific capacity is optimally utilized, and (iii) the network congestion and evacuation time are reduced. The novelty of this study is that it develops a combined dynamic programming-based optimization and traffic microsimulation modelling framework that yields an optimum composition of auto and buses for evacuating a large population while considering both resource constraints (e.g., bus capacity) and the exposures of the population to vulnerabilities.

The study develops a comprehensive 'All Mode Evacuation Decision Support Tool (AMEDST)' that considers population vulnerabilities to allocate all modes of transportation available in the network for evacuation. Therefore, the objectives of this study are to (i) develop an agent-based All-Mode Allocation Module (AMAM) accounting for the vulnerabilities to which the evacuees are exposed, and their mode-specific capacities, and (ii) utilize a traffic evacuation microsimulation model that implements evacuation scenarios and feeds the AMAM with information regarding network supply sufficiency (i.e., bus capacity) to facilitate optimization of the bus allocation. This study formulates a dynamic Knapsack problem (Pan and Zhang, 2018) where bus capacity represents the component "Knapsack" and vulnerability is the component to be maximized. The maximization of the vulnerability scores indicates that people with higher exposure to vulnerabilities are prioritized for bus allocation. A vulnerability score comprising social and mobility vulnerability measurements obtained from a vulnerability assessment model (Alam and Habib, 2019) is utilized to demonstrate the degrees of individuals' exposure to vulnerabilities. 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 combined AMAM and traffic microsimulation model optimally use all modes for evacuation. All modes in this study refer to those modes available in Halifax, which include cars and buses. Trucks are mainly used for commercial purposes, and no current plan is in place to use trucks and trains for evacuations. However, the traffic microsimulation model can incorporate multiple types of modes for simulation, including light rail, truck, and train, among others. The optimization can also be performed for each mode using the mode-specific demand. Traffic operation outputs by modes can be obtained from the simulation model, which feedback the All-Mode Allocation Module. This research will help emergency professionals identify the optimum resource allocation plan for an efficient evacuation following an iterative approach. The results are beneficial 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 the traffic evacuation microsimulation model demonstrates an improvement of overall evacuation performance in terms of network clearance time and the performance of traffic flow indicators.

## 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, including traffic congestion and proposed improvement strategies to make evacuations efficient and safer (Naghawi and Wolshon, 2011; Abdelgawad and Abdulhai, 2009; Wolshon, 2002; Urbina, 2002; Ng, and Waller, 2009). During the 2005 Hurricane Katrina in New Orleans, evacuation primarily relied on automobiles. The evacuation plan implemented for this hurricane did not consider the use of all modes, including public transit and school buses. As a result, a mammoth auto traffic fleet created unprecedented traffic congestion. This congestion caused vehicles to run out of fuel due to long clearance times of approximately 20 hours, leaving 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 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, bus-based, and multi-modal 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 the literature. Since Hurricane Katrina, several studies have 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 the allocation of any available mode, including buses, to whoever needs them by any logical means. Instead, the study solely focused on transit network operation and how to improve bus evacuation. 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 further enhance bus 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 study's objective 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 populations;

however, the evacuation scenario that utilized buses to evacuate the carless population experienced no changes in terms of traffic impacts. Nevertheless, there is a significant knowledge gap 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 is not adequately addressed in these studies include (i) access to all transportation modes for all evacuees so that they can choose specific modes based on their needs or uncertainties that may appear amid evacuation, and (ii) the desired 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, 2006). Otherwise, the sudden spike in traffic demand may create large-scale congestion. Consequently, should it be either vehicular traffic or buses, people could be stranded on the road as it occurred in Houston during the Hurricane Rita evacuation (Renne et al., 2008; Zhao et al., 2010).

This study fills this gap by developing a novel framework to utilize all modes in an evacuation and estimate an optimum auto-bus mix composition that improves 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 the evacuees to different vulnerabilities, including mobility vulnerability obtained from the traffic microsimulation model used in this study.

According to a national hurricane survey in the US, most cities do not have a sufficient number of buses to evacuate carless and transit-dependent populations leading to a limited bus capacity situation (Wolshon et al., 2001). For example, during Hurricane Katrina's evacuation, only a quarter of estimated buses were available to evacuate carless populations (Litman, 2006). The issue is even more critical when considering a bus-based evacuation of the residents in need of transportation assistance. Moreover, the risk of flooding of buses or driver unavailability may be significant, as occurred in New Orleans during the evacuation (Renne et al., 2011; Litman, 2006). Although a bus-based evacuation may not be as successful as planned and predicted due to various risks, there is an immediate demand to develop an optimal bus allocation plan to make bus operation reliable and earn the evacuees' credence on the bus service during an emergency. Given the evidence of the limited bus availability in most jurisdictions, this study formulates an evacuation problem under a limited resource condition. The resource allocation problem for an evacuation involves two components: demand (resource receivers/evacuees) and resource constraints (e.g., bus capacity) that change with the progression of evacuation time. When demands at different evacuation times and the measurements of evacuees' exposure to vulnerabilities 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 the prioritization of individuals with higher vulnerabilities, and the limited resources (i.e., bus capacity) are optimally utilized. Several widely used combinatorial optimization problems include the Traveling Salesman, Vehicle routing, and Knapsack problems. A Knapsack problem involves maximizing the number of items (e.g., evacuees) and item values (e.g., vulnerability scores) while the Knapsack capacity (e.g., bus capacity) must be satisfied. Therefore, 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 unfortunately, there is no known polynomial solution algorithm to solve this nature of problem that is fast and exact (Cormen et al., 2009; Welch, 1982). However, there are several solutions that can solve NP-complete problems in polynomial time, including the 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 that 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 items: accept or reject. Thus, the complexity of this algorithm grows exponentially following $O(2^n)$. Due to complexity, this algorithm is suitable for small Knapsack problem instances, while evacuation often 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 the exponential complexity (Hristakeva and Shrestha, 2005; Goerigk et al., 2014). However, the Dynamic Programming (DP) algorithm appears to be more suitable for solving a Knapsack problem. DP is efficient in dealing with the problems involving the re-occurrence of sub-problems. It computes a sub-problem only once and stores it in a table for later use. Thus, the algorithm efficiently reduces computation time by avoiding the solving of recurrent sub-problems each time. Moreover, it can efficiently be used until the capacity is less than the demand, which represents an evacuation condition. Therefore, this study adopts a Dynamic Programming algorithm for solving the proposed combinatorial optimization problem. This study will also improve the solution approach using DP to solve a large-scale evacuation optimization problem, while algorithms are used to solve other large-scale evacuation problems (Kulshrestha et al., 2014; Goerigk et al., 2014; Alam et al., 2019) may suffer from exponential complexity or local optima.

This study establishes a feedback loop between optimization and traffic microsimulation models within the proposed AMEDST. Optimization results are used in a traffic microsimulation model to determine whether any improvement in evacuation operation is achieved and/or if the fleet capacity is exhausted. The 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 of the criteria mentioned above. The proposed AMEDST will help emergency managers and professionals iteratively evaluate contrasting evacuation scenarios involving resource allocation to reach an optimal decision.

## 3. Methodology

This study develops an 'All-Mode Evacuation Decision Support Tool' framework, which accounts for evacuees' exposure to different vulnerabilities and mode-specific capacity in the vehicle allocation process for a mass evacuation. The 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 models, 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 the 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 scenarios and update AMAM with bus capacity information for sequential scenario testing and evaluation. The study uses a scoring 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, 2019). The mobility vulnerability is estimated based on the average time required to travel from an origin zone to destination shelters. The traffic microsimulation model calculates 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 1 presents an overall framework of the proposed AMEDST.

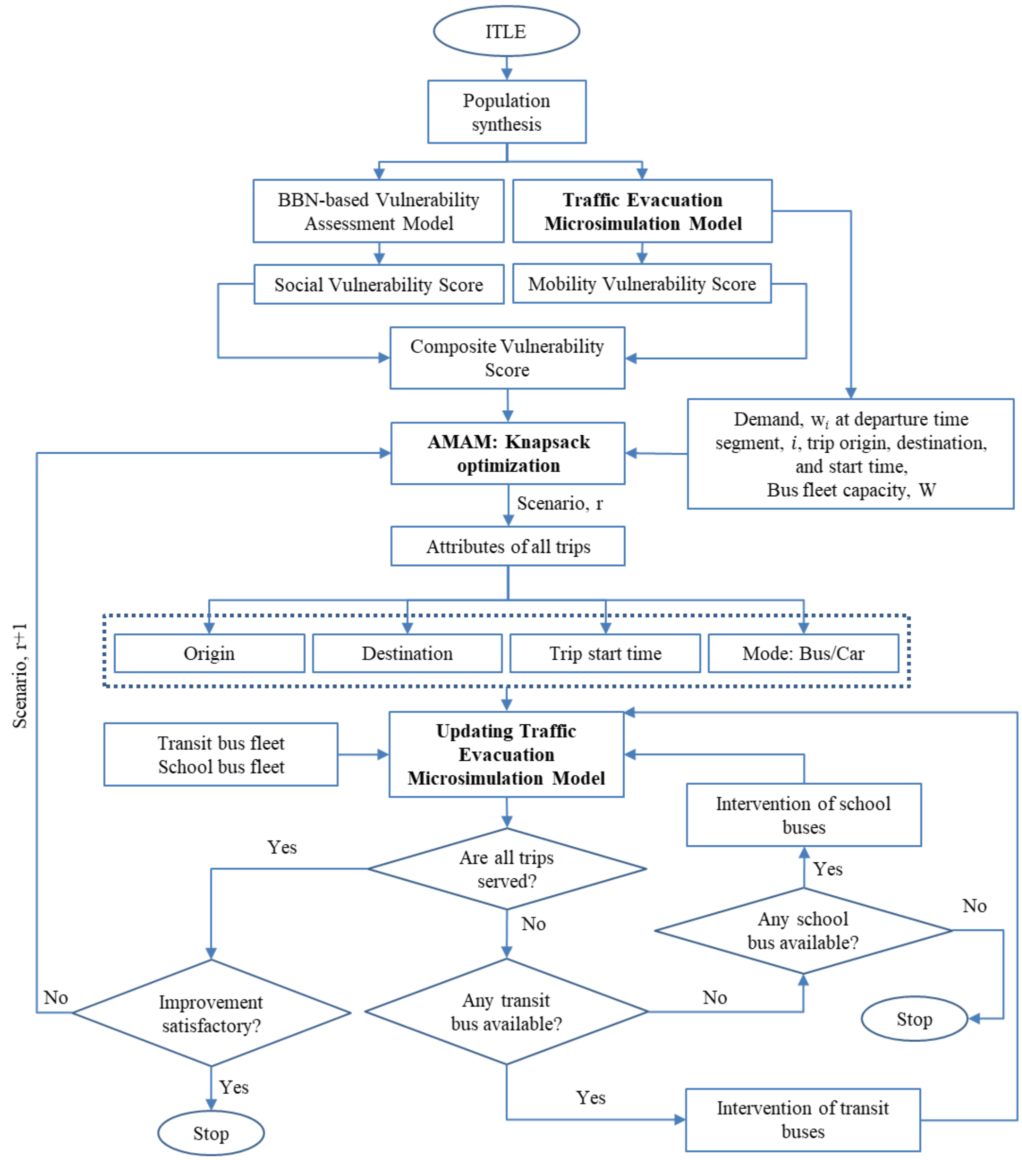



*Figure 1: A Framework of All-Mode Evacuation Decision Support Tool (AMEDST)*

### 3.1. Knapsack Problem Formulation

This study formulates a combinatorial optimization problem called "Knapsack problem" aiming to best utilize the available Knapsack capacity (i.e., bus capacity) while prioritizing the maximum number of vulnerable evacuees for bus allocation. Let $C$ 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, $q_i$ obtained from a traffic evacuation microsimulation model. 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:

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

Subjected to:

$$\sum_{i \in n} q_i \leq C \tag{2}$$

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

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

Knapsack problem is an 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. The uniqueness of this algorithm is that it stores the solution of sub-problems for recursive for later.

### 3.1.1. Dynamic Programming for Sub-Problem Formulation

Dynamic programming algorithm develops a matrix, $K$ with a dimension of $n+1$ rows and $C+1$ 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. At this point, the obtained Knapsack value 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:

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

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

$$K[0][r] = 0 \text{, when } K[i][0] = 0 \tag{6}$$

$$r = \{0,1,2,3.......,C\} \tag{7}$$

Finally, the values corresponding to $K[s][C]$ represent the Knapsack value calculated by 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 study also adds a function used 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:

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

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

## 3.2. Traffic Evacuation Microsimulation Model

This study utilizes a traffic microsimulation model developed by Alam et al. (2019). The model combines an auto and a bus road network for a mixed traffic evacuation of Halifax, Canada. A brief description of the model is presented below for a better understanding of its components and functions.

### 3.2.1. Transport Network Model

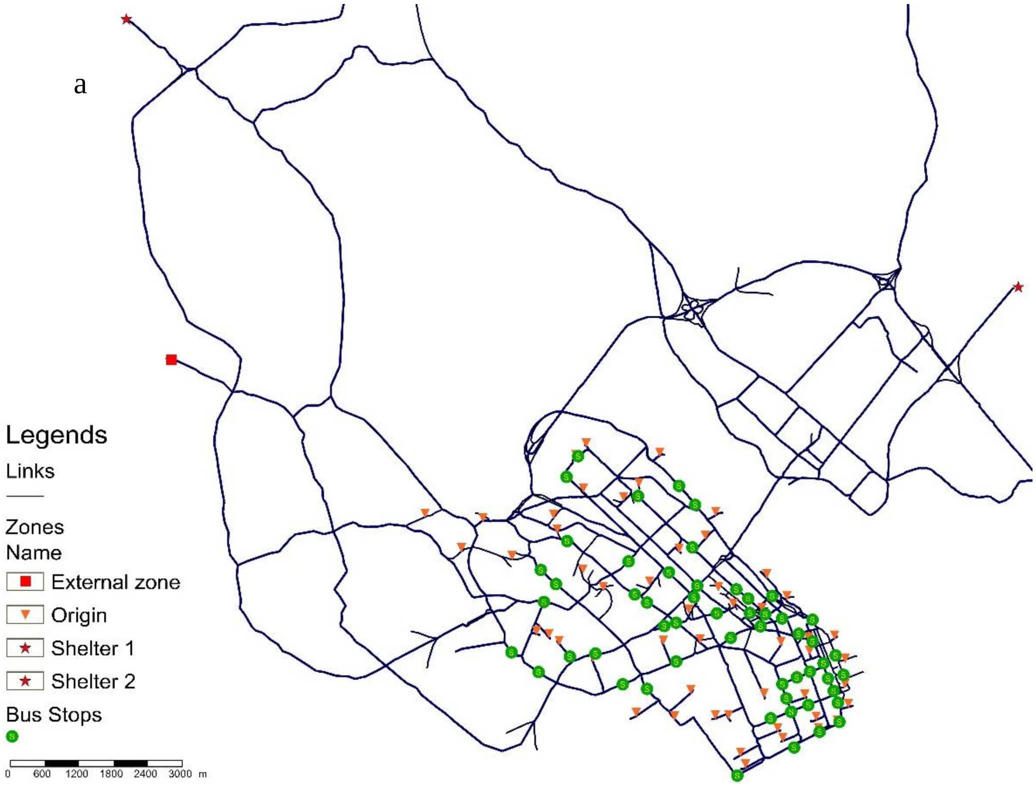
Auto Road Network Elements – The transport network is modelled at a finer level within PTV's VISSIM platform. Links and connectors are coded in detail and include geometric information, permitted vehicle types and classes, and permitted driving maneuvers, for example, lane change and restrictions. The model includes 1784 links and connectors to represent the Halifax transport network. Traffic analysis zones are represented by using parking lot command in the microsimulation model. Parking lots are the origin and destination of an OD pair, and a zone may comprise multiple parking lots. In total, 111 parking lots are built in the model to represent 56 traffic analysis zones, two evacuation shelters, and one external zone representing a friend's or relative's place. Note that multiple parking lots in the simulator can represent a zone. Figure 2a illustrates road network elements within the traffic microsimulation model.

Transit Road Network Elements – Transit network consists of transit routes and pick-up and drop-off points (see Figure 2a and Figure 2b). The model includes twelve transit routes (see Figure 2b) and 135 bus stops obtained from Alam et al. (2019).

### 3.2.2. Traffic Controls

Traffic controls are placed on the road network to avoid vehicle-vehicle and vehicle-pedestrian conflicts during traffic movements in the microsimulation model. The microsimulation model includes all the necessary traffic control measures such as signal and stop sign-controlled intersections, priority rules, reduced speed areas, and traffic lights with phase and split time. There are 41 intersections, and each of them contains a signal controller. The signal controller operates traffic lights at an intersection based on the distribution of green-amber-red time across approaches. A command in the model "Conflict Areas" is used to resolve turning conflicts at the intersections. Alam and Habib (2020) provided a detailed description regarding the intersection of the traffic microsimulation model.

a




b

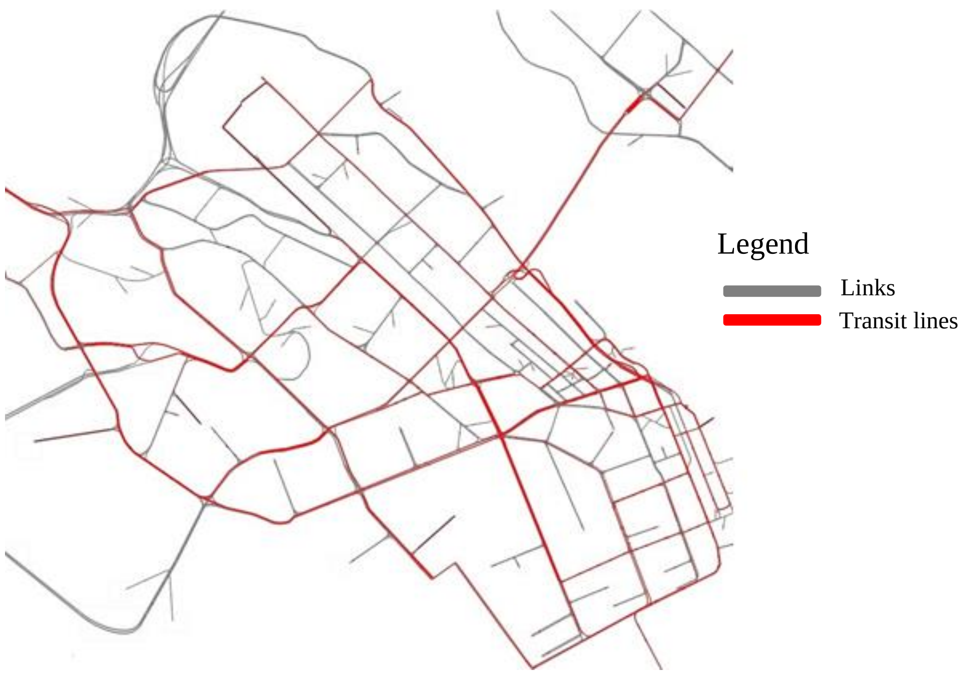



*Figure 2: a(top), and b(bottom): (a) Road network elements of Halifax transport network, including bus stops in traffic microsimulation model, and (b) Bus routes obtained from the optimization study by Alam et al. (2019).*

### 3.2.3. Vehicle Loading into Traffic Microsimulation Model

Vehicles are generated following a Poisson distribution based on an average time gap between two consecutive vehicles. Each vehicle is assigned a route based on the traffic congestions in the network. The route assignment process is facilitated by the DTA process described below.

### 3.2.4. Dynamic Traffic Assignment

The traffic simulation model follows a dynamic traffic assignment process to capture dynamic traffic congestion and subsequent route choices in the network. The model evaluates traffic conditions at a given time interval and updates the driver's decisions accordingly. The required inventories to perform DTA include origin-destination matrix, simulation parameters such as the maximum number of iterations, convergence criteria and its tolerance, and additional cost components such as link surcharges. At the starting iteration of DTA, distance is used as a proxy of travel time to search for the best routes. Travel time is repeatedly calculated from sequential iterations and used for path search. The study utilizes equation 9 (PTV, 2014) for travel time estimation at the given evaluation interval during simulation. Suppose a vehicle operates on an edge for more than one evaluation interval. In that case, the model continues measuring the travel time for that vehicle, thus carrying forward the congestion effects with the progression of time in the network. The DTA process is iterated until the convergence criteria are satisfied. Convergence criteria includes minimizing the deviation in traffic flow indicators, for example, traffic volume, and edge travel time between consecutive iterations.

$$Tr_i^{n,j} = \left(1 - \frac{1}{K+n}\right) * T_{r_i}^{n-1,j} + \frac{1}{K+n} * Tm_i^{n,j} \qquad (9)$$

Where, $K$ measures the number of preceding iterations that has have effects on the current iterations

$i$ represents the iterations

$n$ represents the evaluation interval

$j$ represents edge

$Tm_i^{n,j}$ is the measured travel time at iteration, $i$, evaluation interval, $n$ at edge $j$

$Tr_i^{n,j}$ is the smoothed travel time at iteration, $i$ evaluation interval, $n$ at edge $j$ that will be used for path search in the next iteration

### 3.2.5. Calibration and Validation of the Model

Once the vehicle assignment process is settled, the next task is to calibrate and validate the model. Alam et al. (2018) conducted an extensive calibration of driving behavior parameters

(Wiedemann, 1974; Olstam and Tapani, 2004; Miller, 2005) and validated the model based on the observed traffic count at key intersections and different link locations in the network. A Latin Hypercube Sampling (LHS) is used to generate different combinations of the values of driving behavior parameters to identify the desired combination that resembles actual driving behavior in the network. Figure 3 illustrates an overview of the calibration and validation process of the microsimulation model.

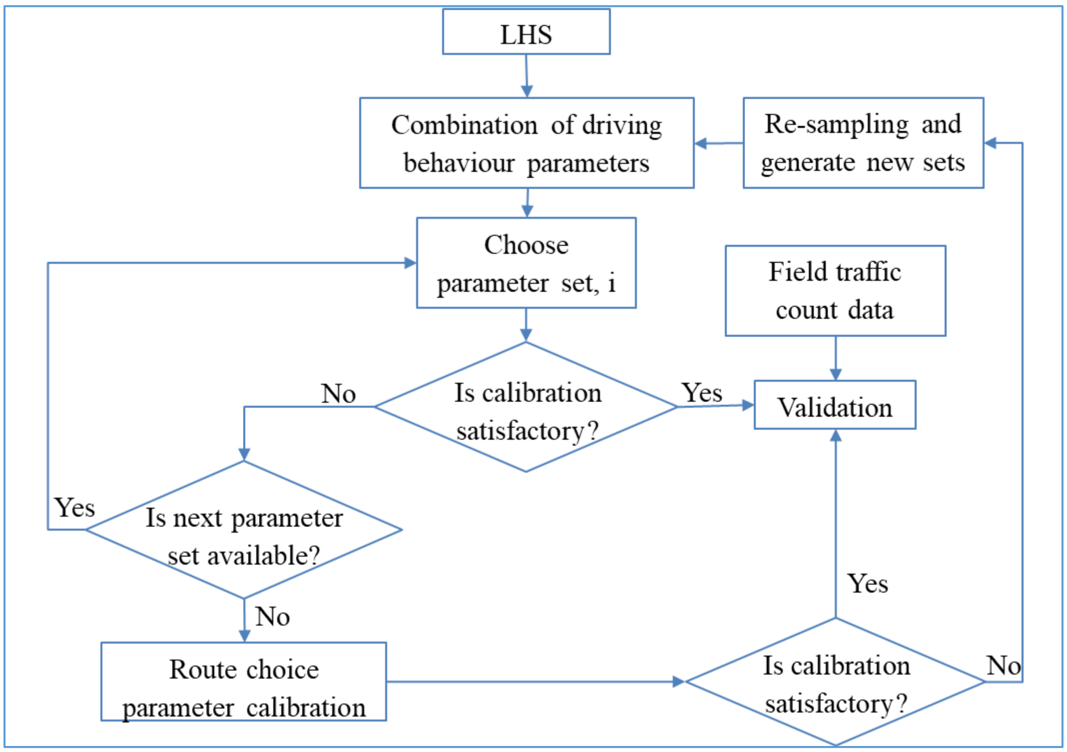



*Figure 3: Calibration and validation of the traffic microsimulation model*

Simulation is conducted to identify the best combination in terms of network performance for each combination of driving behaviour parameters. The driving behavior parameters' calibration focuses on the driver's following behavior, which is governed by the safety distance for driving obtained from equation 10. The combination resulted from driving behavior parameter calibration yields a value of 1.0 for average standstill distance, 0.6 for additive part of safety distance, and 0.7 for multiplicative part of safety distance.

$$d = ax + bx \tag{10}$$

Where, $d$ is safety distance

$ax$ is average standstill distance

$bx$ adjusts time requirement values which can be written as:

$$bx = (bx\_add + bx\_mult * z) * \sqrt{v} \quad (11)$$

Where,

$z$ is a value of range [0, 1], which is normally distributed around 0.5 with a standard deviation of 0.15, and $v$ is vehicle speed

Further improvement of the model is conducted through a route choice parameter calibration. A link surcharge method is utilized to adjust traffic volume if any link anticipates a volume deviated from the observed. Two data sets are used for calibration and validation purposes, respectively. The data was collected by the Halifax Regional Municipality using Miovision cameras for a normal typical day traffic condition and contains traffic counts at one hundred and two locations. The goodness-of-fit of the model in terms of $R^2$ values are 0.81 and 0.82 for two morning peak periods, respectively.

The simulation is conducted for 73,400 evacuees, where 8400 evacuees are transit-dependent and must use a bus for an evacuation. On the other hand, the proposed vehicle allocation process would identify individuals from the rest of the 65,000 evacuees for being evacuated by bus. The traffic microsimulation model informs AMAM with fleet capacity information for optimization and estimates evacuation time and network performances for sequential evacuation scenario analysis.

## 4. Scenario Testing and Evaluations

This study comprehensively tests scenarios of mass evacuation on the Halifax Peninsula within the traffic simulation model developed by Alam et al. (2019). The study revealed that it takes 22 hours to evacuate the Halifax Peninsula without any countermeasure applied. This study develops an improvement scenario that utilizes buses to accommodate for different levels of evacuation demands considering population vulnerabilities and available fleet capacity. Four scenarios are developed where buses are allocated to an incremental demand across scenarios to improve evacuation times and network performance gradually. 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 to develop sequential scenarios, 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 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 bus capacity from the traffic microsimulation model, vulnerability scores from the

Bayesian Belief Network-based vulnerability assessment model, and simulation results. The simulation results for four scenarios are evaluated and compared with respect to a base case scenario. Base The base case scenario represents the evacuation by auto and transit while transit is used only to evacuate people who do not have cars or other options for evacuation.

## 5. Results and Discussion

### 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. School buses are called within the traffic microsimulation model if the transit fleet capacity is exhausted in a scenario. Table 1 lists all sequential scenarios tested and evaluated within AMEDST. All scenarios are compared to a base case scenario taken from the evacuation study by Alam et al. (2019) for the same study area, which revealed that it takes 22 hours for an auto-based evacuation of the Halifax Peninsula. The improvement in clearance time considering the auto-bus evacuation scenario is significant, ranging 9-22.7% with respect to the earlier auto-based evacuation scenarios, as shown in Table 1. The results from the scenario analysis reveal that traffic congestion can be improved by reducing vehicular traffic by 3.9-7.7% from the network with a bus evacuation of 5-20% of individuals that are prioritized based on their vulnerabilities. Moreover, in the earlier study (Alam et al., 2019), 8400 transit-dependent people were evacuated by buses while it is 21,400 for the proposed all mode evacuation case, an increase of 61%. Figure 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 4a to Figure 4d.

*Table 1 Bus Allocation Results and Network Performances*

| Scenarios | Individuals allocated bus | 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 demonstrate the effectiveness of AMEDST in considering all modes for evacuation. Except for scenario 1, the AMEDST utilizes school buses to accommodate the target demand for evacuation when municipal bus capacity is exhausted. Note that the optimization model in this study produces results for the best case, and does not reflect the uncertainty in bus evacuation, including the uncertainty in demand and bus capacity. However, this study provides a range of the evacuation performance. For example, the highest demand scenario provides the lower limit, and the base case scenario provides the upper limit of the evacuation time in this study. The range can be the basis for the evaluation of other bus evacuation scenarios considering the uncertainty.

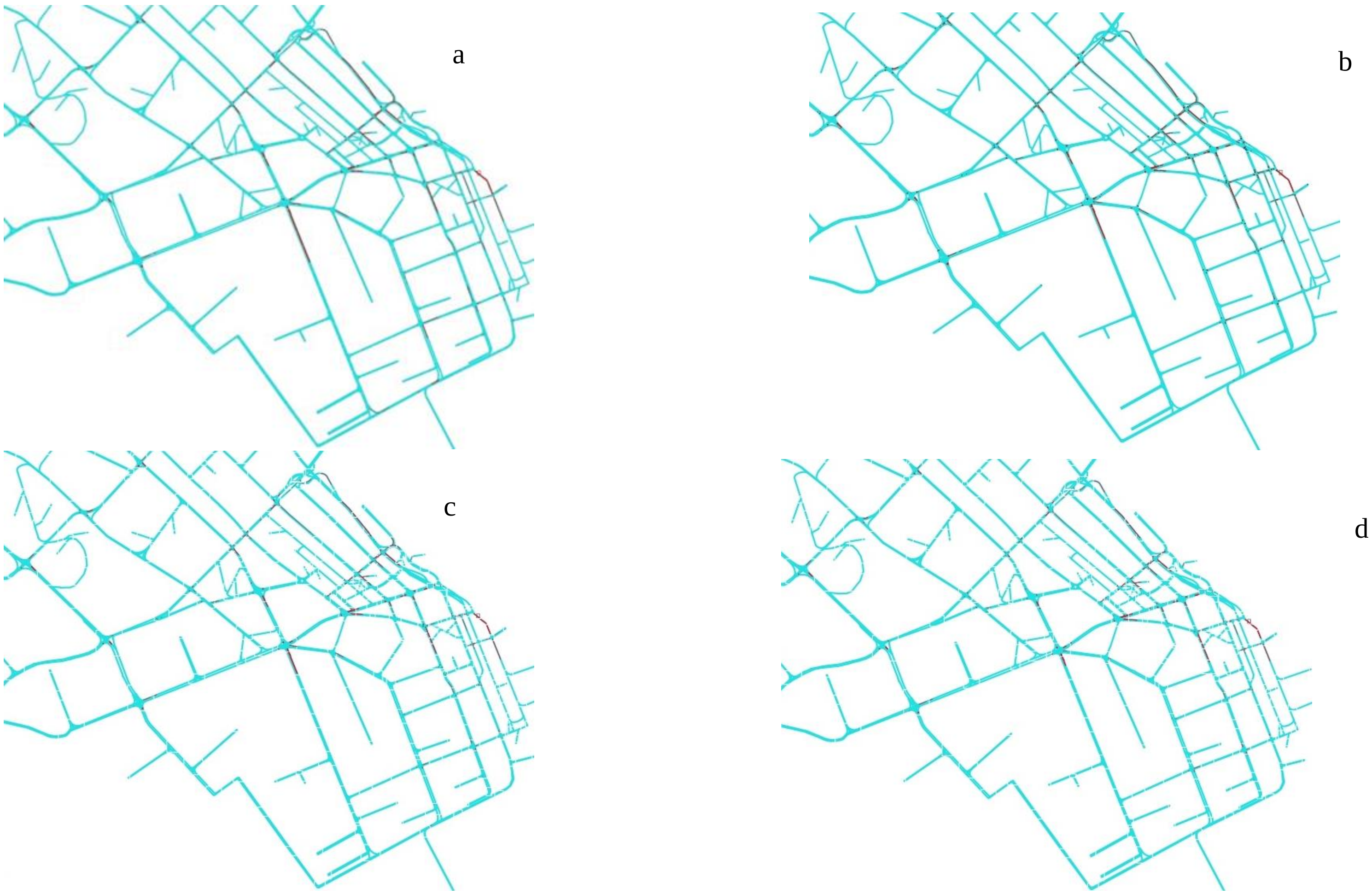



*Figure 4: a (top-left), b (top-right), c (bottom-left), and d (bottom-right) Average queue length measured in four vehicle allocation scenarios where (a) Scenario 1- 5% demand, (b) Scenario 2- 10% demand, (a) Scenario 3- 15% demand, and (a) Scenario 4- 20% demand*

The results in Table 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 high cost to deploy 410 (322 transit buses +88 school buses) buses. They may also select scenario 1 which only involves 193 municipal buses but demonstrates a small evacuation time improvement. 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 the remaining fleet capacity can serve more individuals. Decision-makers can easily evaluate municipal budgets and require lee way time to safely evacuate people when choosing a scenario.

## 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 5 shows the percent of individuals that are assigned to a bus while accounting for different vulnerabilities.

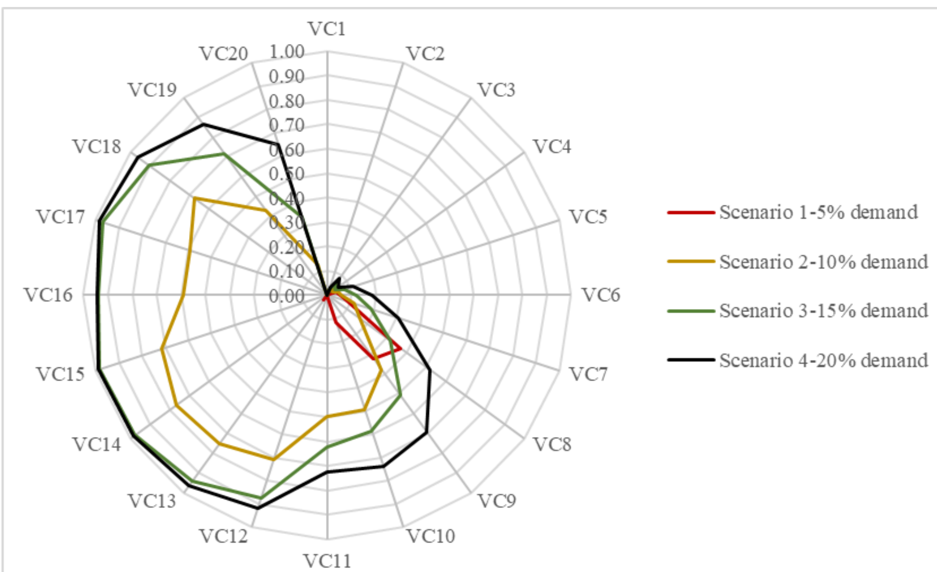



*Figure 5: Percent individuals assigned to buses based on different vulnerabilities*

The results suggest that the percent individuals prioritized across zones for bus allocation comprise 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 of individuals 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 5% demand does not reasonably reflect the distribution of the vulnerable population. The results suggest that it requires at least a 10% demand consideration to reflect a reasonable distribution of the vulnerable population when allocating buses to evacuees from a wider area for evacuation.

### 5.3. Addressing of Vulnerabilities across Planning Districts

This study examines the vulnerability characteristics of individuals who might be allocated buses for their evacuations. The study area has been sub-divided into four planning districts “Downtown (DT),”, “West-End (WE),”, “North-End (NE),” and “South-End (SE)” for analysis purposes. Figure 6a and Figure 6b show the vulnerability scores of individuals of different planning districts who are allocated buses for their evacuations in scenario 3 and scenario 4. Scenario 1 and scenario 2 serve a smaller demand and do not encompass all planning districts while prioritizing individuals with higher vulnerabilities. For example, scenario 1 with a target demand of 5% only prioritizes individuals from DT for bus allocation.

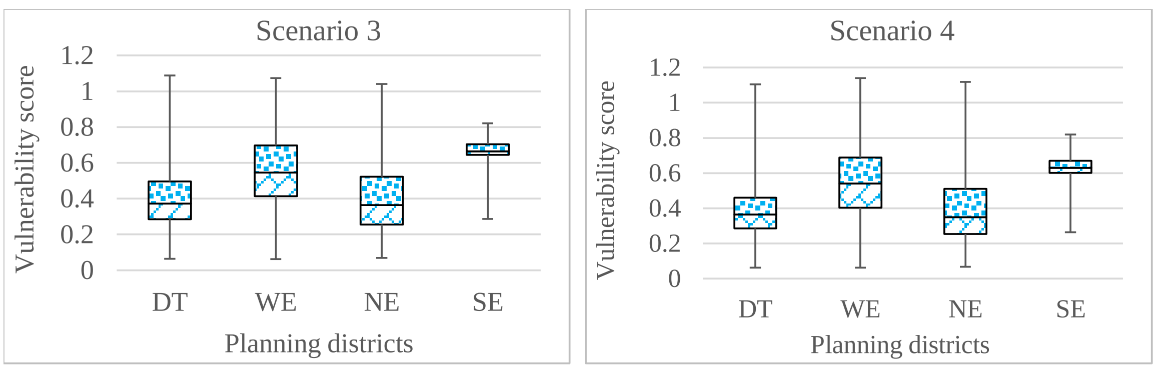



*Figure 6: a (left), and b (right) Vulnerabilities accounted for bus allocations across planning districts in (a) scenario 3-15% demand, and (b) scenario 4-20% demand.*

The results suggest that the only difference between Figure 6a and Figure 6b is that the upper whisker in Figure 6b is relatively longer in the case of NE and WE. The reason is that due to the increase in the target demand, more people from different zones become eligible for bus allocation based on their urgency.

### 5.4. Addressing of Vulnerabilities across Planning Districts

This study identifies the critical time segments of an entire evacuation period when it demands bus allocation to improve overall evacuation operations. Figure 7a to Figure 7d illustrate the time segments when individuals have been assigned to buses.

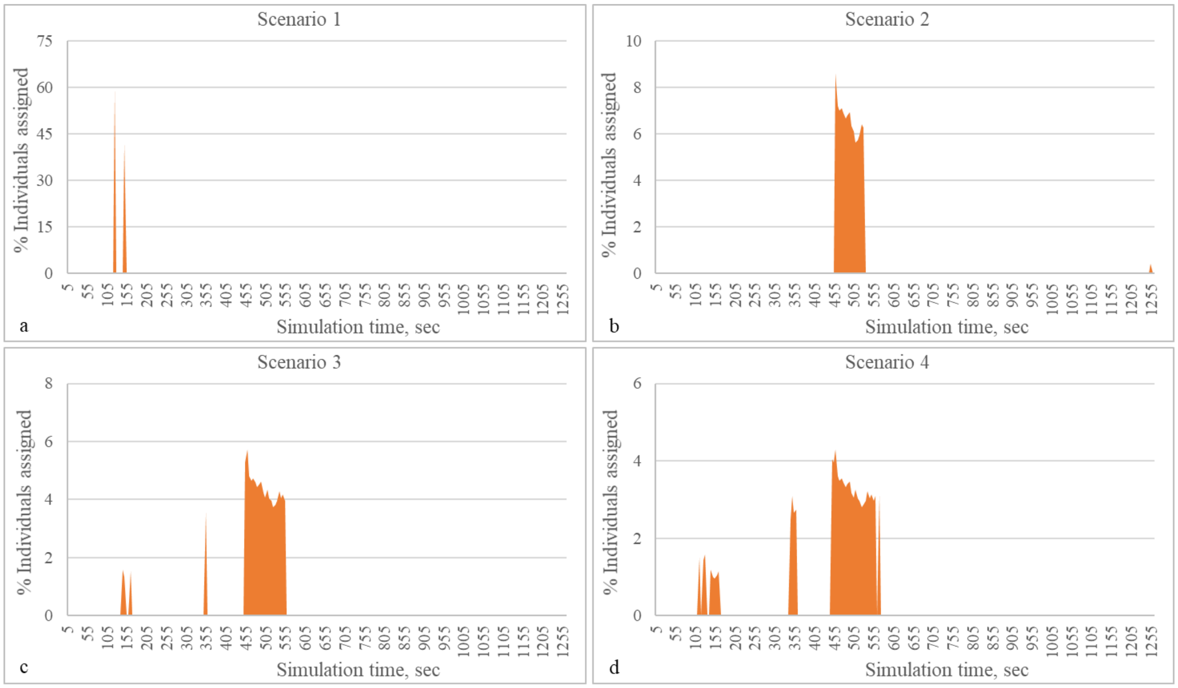



*Figure 7: a (left-top), b (right-top), c (left -bottom), and d (right-bottom) Time segments of an evacuation period that assigns buses to individuals under four scenarios (a) Scenario 1 –5% demand, (b) Scenario 2 – 5% demand, (c) Scenario 3 – 5% demand, and (d) Scenario 4 – 5% demand*

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 7a and Figure 7b). On the other hand, in scenario 3 (15%) and scenario 4 (20%), buses were allocated to individuals at different time segments to encompass a greater demand from a wider area. The results have certain policy implications in helping decision-makers identify critical time segments of an evacuation. For example, when individuals need transportation the most and how effectively the demand can be accommodated given the limited capacity of buses.

## 6. Conclusion

This study presents a novel framework of an All- Mode Evacuation Decision Support Tool that combines an All-Mode Allocation Module and a traffic evacuation microsimulation model. The contribution of this study is that it recognizes all modes, particularly transit and school buses in evacuation operations and determines an optimum auto-bus composition for conducting an efficient evacuation in the transport network. Methodologically, the study contributes to solving a mode allocation optimization problem by implementing a Dynamic Programming algorithm. In contrast, several solution algorithms used in solving other evacuation problems may suffer from local optima or exponential complexity. This study also provides a comprehensive approach to mass evacuation microsimulation modelling and scenario testing.

The study considered a case study of Halifax, Canada to demonstrate the efficacy of the developed AMEDST 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 vulnerability are prioritized for allocating evacuation buses in all scenarios. The developed tool can identify the critical time segments of an entire evacuation period when bus allocation is critical in improving 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% are achievable. This results in a 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 achievable 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 AMEDST support this study's objective and the rationale for developing a tool that recognizes the role of all modes in evacuation operations.

This study has some limitations. For example, the study utilized a DTA module that does not include the drivers' path choice learning process for panicked traffic conditions. It reflects normal day traffic congestions and the subsequent drivers' responses considering a normal state of mind. It would be interesting to develop an enhanced DTA module to optimize travel outcomes where a panic situation can be considered within the path choice algorithm. The study also does not consider losing bus fleet capacity due to the possibility of buses being flooded or failed due to any other uncertainties amid evacuation. Moreover, this research used bus demand from a regional transport network model; however, external factors, including final-destination of bus-based evacuees, last-mile transportation, provision to accommodate staffs and pets in the bus, bus fares and pick-up locations, may influence the evacuees' willingness to adopt bus as their evacuation modes. Future studies should include the abovementioned criteria in forecasting demand for bus evacuation. The study also does 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 AMEDST.

In closing, this study addresses the gaps in evacuation literature by considering and implementing the roles of all modes in evacuation operations. The tool 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.

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