EFFECTS OF CONNECTED VEHICLE TECHNOLOGY ON MOBILITY AND MODE CHOICE

EFFECTS OF CONNECTED VEHICLE TECHNOLOGY ON MOBILITY AND MODE CHOICE

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Abstract

Connected vehicle is a fully connected transportation system in which vehicles, infrastructure, and mobile devices are enabled to exchange information in real-time to bring advancements in transportation operations. It is important to incorporate the new characteristics of the connected vehicle in the transportation planning process. Also, it is vital for planning and road agencies to better understand the impacts of connected vehicle on transportation networks, system demand, and travel behavior of road users in order to properly prepare for them. In addition, developers of connected vehicle systems can gain insight into how their systems will impact road users and network performance. When a change in performance of a transportation network occurs it can potentially cause users to change travel modes, known as mode choice. In this research, the change in mode choice, due to the change in network performance by introduction of connected vehicle is studied. This provides a more accurate depiction of the performance of the network and indicates how connected vehicles could change travellers' preference in travel mode. The effect of this technology is explored on the performance of the Toronto waterfront, in a microsimulation environment. The results show that average travel time increases for high market penetrations when a dynamic route guidance algorithm is implemented, a phenomenon that occurs in dense, and complex traffic networks. Analysis of mode choice shows a loss in the auto mode share, for high market penetrations, due to the increased auto travel times. This loss in the auto mode share is compensated by increases in the other modes.

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Acknowledgements should also be made to thank Dr. Baher Abdulhai of the University of Toronto, for permitting the use of their Toronto Waterfront microsimulation network for the use of this thesis. This was likely the only network that could meet the needs of this research and all the work that went into developing it is greatly appreciated. In addition, thanks go to many others professors and graduate students that helped through the courses taken with them, providing the author with the background knowledge needed to produce this thesis.

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Publication List

This thesis consists of the following papers:

Paper I

Minelli, S., Izadpanah, P., Razavi, S., 2014. Evaluation of the Impact of Connected Vehicle on Mobility and Mode Choice. (Submitted to the Journal of Advanced Transportation, July 2014, Submission ID: ATR-14-014)

Co-Authorship

This thesis has been prepared in accordance with the regulations for a "Sandwich" master's thesis, and includes a paper where multiple authors are credited. This section outlines the role of these authors.

Chapter 2: Evaluation of the Impact of Connected Vehicle on Mobility and Mode Choice

The literature review, methodology, implementation and analysis were performed by Simon Minelli. The development of the paper was accomplished by Simon Minelli under the guidance of Dr. Saiedeh Razavi. The paper was reviewed and edited by Dr. Razavi and Dr. Pedram Izadpanah.

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1. Thesis Summary

1.1. Introduction

Connected vehicle has the ability to change transportation in a fundamental way. Previous to the connected vehicle, each individual traveller was relatively isolated from other vehicles and were not able to gain anything from the experiences of others. Attempting to overcome this, many methods have gained popularity in informing travellers of what others are experiencing, and therefore, what they may experience if they make similar decisions. Connected vehicles attempt to bridge this gap by allowing the transfer of information from vehicle to vehicle (V2V) as well as to and from vehicles and infrastructure (V2I). This allows for a nearly limitless number of uses, including the realms of safety, mobility, environment and entertainment.

This work assess the potential impact of connected vehicles, on mobility as well as mode choice. Introducing connected vehicles to a transportation network changes the performance of the network. This change in performance causes travellers to reassess their choice in travel mode, known as mode choice. A change in mode choice changes the demand on the network, which again changes the performance of the network. This turns into an iterative process which converges and determines the equilibrium state of the network after connected vehicles are introduced. Incorporating mode choice not only allows for the analysis of change in demand but also provides a more accurate view of network performance after the introduction of connected vehicles.

This study uses dynamic route guidance, aimed at improving mobility. With dynamic route guidance, vehicles record travel times as they traverse a transportation network and send these records to other vehicles. These vehicles use the records to find the fastest path through the network.

Understanding the impact that connected vehicles can have on transportation networks is imperative to the stakeholders involved. For planners and road agencies, it allows them to properly prepare for potential change. It also allows technology developers to create a design that produces the desired outcomes.

1.2. Background

1.2.1. Demand Modelling

Demand modeling is a tool used to assess the changes in demand on a system, often brought about through changes in supply of the system. Examples could be the addition or removal of a highway or a new development. Once a change in demand has been identified, the performance of the system can be reassessed. Areas of demand that are often examined include changes in population, land use and mode choice.

The study on travel demand is constantly being expanded upon in order to cover new situations. With telecommuting becoming more prevalent, demand models are being used to see how this will affect areas such as mode choice (Nurul Habib K. K., 2011). In addition, researchers have simulated and observed the effects that social influence has on telecommuting, finding that marginal adaptors are influenced heavily by others (Paez & Scott, 2007). Off-peak times, such as weekends, have not been a large focus of demand analysis thus far, but some are attempting to create models that accurately represent and inform off-peak hours (Kato, et al., 2011). Due to increased safety standards, many areas are looking at mass evacuation methods and demand models have the ability to effectively capture these scenarios (Montz, et al., 2013). Tourism can also create a large amount of trips in certain areas and demand analysis is able to provide insights into these changes (Ren, et al., 2009).

However, traditional demand analysis does suffer from limitations. Some studies have found that it can be difficult to accurately set cost values, which must be set correctly in order to justify the assumption that the user is an optimal decision-maker (Williams, 1977). Others argue that these models can make inconsistent considerations of travel times and congestion effects while combining different models can overcome this problem (Yang & Chen, 2009). To overcome some of these problems, research is underway on the relationship between supply of the network and demand of the users (Castiglione, et al., 2012).

Of particular interest to this study is mode choice modelling, designed to determine the split between various modes. Logit models use the assumption of random utility theory, assuming users are more likely to choose a mode that maximizes their utility (Washington, et al., 2001). Utility is often defined using parameters including, but are not limited to, travel time, access to modes or income. Aspects such as parking cost, parking type and social interactions are recently being fit into mode choice models in order to have a better representation of why people make these choices (Nurul Habib, et al., 2012; Smirnov, 2010).

1.2.2. Traffic Assignment

It is necessary to assign vehicles to the routes that each vehicle takes throughout the network, known as traffic assignment. This involves mimicking decisions made by the travelers in the network, motivated by many aspects such as performance of the network and behavioral factors. For viewing travel demand on a large geographic scale, a macrosimulator is often used for the task of traffic assignment due to a lower computational demand. Macrosimulators traditionally assign traffic using either a user optimal or systems optimal strategy. In a user optimal strategy it assumed that the each user selects a path that minimizes their individual cost. A system optimal strategy assumes that users choose routes that minimize the total average cost of the network. Although a user optimal strategy is considered to be the more realistic of the two, there are still many assumptions that call into question the practicality. A prominent example is that it assumes users have perfect and correct knowledge of route costs, which they do not unless proper, real-time data is fed to the user. Another assumption is that users are rational and will always choose the route that reduces their cost, however it cannot be inferred with complete certainty how people value certain costs. These issues have been studied (Preshker & Bekhor, 2004) and researchers have attempted to find more accurate assignment algorithms (Bekhor, et al., 2012; Florian, et al., 2009). In addition, neither strategy can capture the dynamic nature of connected vehicle communication or dynamic route guidance. Therefore a microsimulation approach is needed for this study.

Microsimulators, for small scale applications, are generally performed using agent-based models. This means that each agent, or vehicle, in the network is followed, or tracked and realistic driver behavior is attempted. This is more accurate than a static assignment but can be computationally demanding for larger scales and is more sensitive to errors in data. More realistic simulation of driver behavior is constantly being worked on to properly simulate realistic driver action (Chong, et al., 2011). Studies have been done to compare and combine micro and macrosimulation in order to add more realism and versatility to traffic models (Vilaró, et al., 2010; du Plessis & Joubert, 2012; Gao, et al., 2010; Wang, et al., 2010). Some of these studies attempt to expand the use of current micro-simulators (Jayakrishnan, et al., 2003), while other attempt to combine multiple modellers (Hao, et al., 2010; Oh, et al., 2000; Panwai & Dia, 2007).

1.2.3. Paramics Assignment

Quadstone Paramics is a traffic microsimulator that simulates each agent vehicle individually for the purpose of traversing traffic networks (Paramics, 2013). This simulator is used for traffic assignment in this study. This section will detail the strategy used for vehicles to determine route choice.

In order to make realistic route choices, Paramics vehicles use a cost table. This cost table contains a perceived cost about the links in the network. A vehicle uses these costs to assess the next few route choice decisions it will have to make to get to its destination. It should be noted that vehicles do not prepare a route for their entire destination, rather, only for a few next steps. This is a crucial difference between regular vehicle assignment and connected vehicle assignment.

Costs for each link in the table are developed using Equation 1.1.

$$Cost = aT + bD + cP \qquad \text{Eq. 1.1}$$

Where, T is the average travel time of the link, D is the length of the link and P is the cost of any tolls. a, b and c are coeficients, set by the user, that weight the cost information. The default is set as a being 1 and the other coefficients are set to 0. This is the case for the network used in this study, making the routing responsive to only link travel time.

In order to properly calibrate the network, penalties can be set to simulate real-world situations that are not explicitly modeled in the Paramics network. These include link penalties that add an additional, user-defined cost to a set of link categories (or groups) or penalties applied to specific links.

The cost table is updated after a user-defined period in the simulation. For this time, a balance must be struck between how dynamic the times are and the amount of computing time. In addition, there are two main types of vehicles in Paramics, defined as familiar and unfamiliar. Familiar vehicles are assumed to have knowledge of different routes and have access to updated table costs; while unfamiliar vehicles, do not have updated information available and, therefore, use a predefined route.

Paramics attempts to mimic randomness in the information a vehicle has about travel times. Therefore, Paramics uses a perturbation algorithm, used to introduce randomness into the costs. The formula used can be seen in Equation 1.2.

$$\dot{C} = \left(\frac{100-P}{100} + N\right) C \qquad \text{Eq. 1.2}$$

In Equation 1.2, $\dot{C}$ is the updated cost, C is the original cost, N is a random number from 0 to $\frac{2P}{100}$ and P is the perturbation factor.

1.2.4. Simulation Network

The network used for this study is the southern portion of the Toronto waterfront. The network was provided by researchers at the University of Toronto. Although information about the network is available in paper I, additional information is presented in this section.

Demand estimates were created using a three step procedure based from Transportation Tomorrow Survey (TTS) data. The TTS is a telephone survey of 5% of the Greater Toronto and Hamilton Area, collecting travel information and personal information. A static traffic assignment was performed in EMME/2 macrosimulator for the entirety of the Greater Toronto Area (GTA). The Toronto waterfront portion was then analyzed to ensure that the level of traffic was consistent with real world conditions. As part of this, the speed and capacity of many links were adjusted until reasonably consistent conditions were met. The assignments from this model were then used to develop seed origin-destination demands for the study.

The same GTA EMME/2 model was then used to capture a seed matrix by taking counts of all vehicles entering, exiting, traveling to, or traveling out of the study area. This provided a full origin-destination (OD) matrix for the study area as a starting point to developing an accurate OD matrix for the Paramics network.

These seed demands were then adjusted to overcome problems with the data not lining up with real world situations. More specifically, the OD demands were continually adjusted to meet observed road counts using a gradient method. Overall this produced an EMME/2 assignment that reflected the observed counts and resulted in a 5% increase in the AM peak hour demand, generally for trips originating in the study area.

Multiple methods of network refinement were performed which are briefly touched-upon in this section. Many methods of geometry modification were performed in order to account for areas that were exhibiting unexpected vehicle behavior. These include the removal and addition of nodes, curbs, stop lines, lane choice, sign locations, signal adjustment and zone boundaries. In addition, a number of network-wide parameters were calibrated. The time-step, time between model calculations, was set at 5 seconds, which was found to be an appropriate compromise. A demand profile was created to slowly increase the level of demand over the warm-up period helping to stabilize the network before the data collection period. Since links with streetcars present are known to move slower than other streets, these streets have their speed limit adjusted until a lower speed was met. Lastly, to determine the mean headway between vehicles, mean reaction time, percentage of familiar vehicles, perturbation and feedback time, a genetic algorithm was used.

In the Waterfront network, categorical link penalties have been used to account for things such as pedestrian movement and transit, while individual link penalties have not been used. In the same way, turning penalties can be applied to specific movements but have not been applied to the Waterfront network. Restrictions can also be set for certain vehicle types and movements. These are used in the Waterfront network in order to mimic real-world conditions. For the Waterfront network, a feedback period of 4 minutes is used, meaning cost tables are updated every interval.

1.3. Summary of Papers

This thesis contains one manuscript.

Paper I: Evaluation of the Impact of Connected Vehicle on Mobility and Mode Choice

(Submitted to Journal of Advanced Transportation, July 2014)

The implementation of connected vehicle has an impact on how travellers use the road network and, therefore, the performance of transportation networks. Knowledge of this impact can be useful to many stakeholders including developers of technology architecture and policy makers. This paper aims to analyse these impacts in a large, microsimulation environment; looking at the change in performance of the network and changes in demand, particularly of mode choice. Incorporating changes in demand allows for a more detailed view of network performance as well as the changes in demand of various modes. The results show an increase in travel time for high market penetrations of connected vehicles, if a dynamic route guidance algorithm is introduced. Further study shows this occurs in networks with high levels of complexity, demand and connected vehicles. Analysis of mode choice shows a move away from the auto mode to all other modes. This knowledge can help guide the implementation of connected vehicle.

2. Evaluation of the Impact of Connected Vehicle on Mobility and Mode Choice

Simon Minelli, Pedram Izadpanah, Saiedeh Razavi

2.1. Abstract

Connected vehicle is emerging as a solution to exacerbating congestion problems in urban areas. It is important to better understand the impacts of connected vehicle on network and travel behavior of road users. The main objective of this paper is to evaluate the impact of connected vehicle on the mode choice and mobility of transportation networks. An iterative methodology was used in this paper where demand for various modes were modified based on changes in travel time between each Origin-Destination (OD) pair due to introduction of connected vehicle. Then a traffic assignment was performed in a micro-simulation model which is able to accurately simulate vehicle-to-vehicle communication. It is assumed that vehicles are equipped with a dynamic route guidance technology to choose their own route using real-time traffic information obtained through communication. The travel times obtained from the micro-simulation model were compared with a base scenario with no connected vehicle. The methodology was tested for a portion of Downtown Toronto, Ontario. In order to quantify changes in mode share with changes in travel time associated with each OD pair, mode choice models were developed for auto, transit, cycling and pedestrians using data mainly from the Transportation Tomorrow Survey. The impact of connected vehicle on mode choice was evaluated for different market penetrations of connected vehicle. The results of this study show that average travel times for auto will generally increase and cause a move away from the auto mode for high market penetrations if a dynamic route guidance algorithm is implemented.

Keywords: Connected Vehicle; Vehicle-to-Vehicle; Mode Choice; Traffic Assignment; Mobility; Dynamic Route Guidance

2.2. Introduction

A vehicular ad hoc network (VANET) uses vehicles as communication points in order to create a wireless network. The connected vehicle is a system that uses this concept to create a network with two different types of communication. With Vehicle-to-Vehicle (V2V) communication, vehicles are able to communicate relevant pieces of information with each other, while Vehicle-to-Infrastructure (V2I) allows vehicles to transmit and receive information with infrastructure. Connected vehicle has the potential to improve transportation networks in many ways, including the realms of safety, mobility, environment and entertainment. The particular application that this paper will focus on is dynamic mobility through dynamic route guidance, where vehicles are assigned their route based upon the travel times experienced by other vehicles. Providing vehicles with the most recent and direct information about link travel times should enable vehicles to find the fastest route between their origin and destination through a given network. Connected vehicle, through its applications such as dynamic route guidance, has the ability to change the performance of a transportation network. This change in performance will cause travellers to change their decision about what mode to use. Incorporating this change in traveler mode choice provides a more accurate depiction of network performance after the technology is introduced and depicts the new mode share and multimodal demand. The effect that real-time traffic information and dynamic route guidance has on mobility as well as mode choice will be studied throughout this paper.

Understanding the impact that dynamic mobility and in particular dynamic route guidance may have on a transportation network is important for all stakeholders as it allows them to accurately prepare for upcoming changes. The results of this paper can assist a wide range of stakeholders. For those creating the technology, it may impact how information is collected and used, as poor results could lead to a lack of adoption. For managers of the network, understanding potential impacts can allow them to prepare for predicted changes. Policy makers have the ability to create policy that can incorporate the expected changes into their decisions. This paper presents related work and background, depicts the scope of the study, outlines the proposed methodology and discusses the results.

2.3. Literature Review

Connected vehicle technology enables vehicles to send and receive information in practically real-time. This information is transferred between vehicles and infrastructure, creating a communication network with the technology split into two realms: V2V and V2I. Various types of information can be sent through connected vehicle technology allowing for a vast amount of practical applications. These applications are sensitive to the details of the technology including latency, communication range and market penetration [1] [2].

Currently, many areas of interest are focused on using connected vehicles to make traffic networks safer and more efficient. Researchers have proposed a potential system architecture of connected vehicle for use with safety, noting potential issues such as connection setup time and network configuration [2]. Incident conditions have been looked at in order to improve safety, although this may be at the expense of travel time under high levels of congestions [3]. Forward collision warning systems have the ability to warn drivers of dangerous incoming situations. Connected vehicles have an advantage in this area by only providing warnings to relevant vehicles and providing the information without large delays [4]. In addition to safety, connected vehicles may reduce energy consumption by optimizing signal timing and headways [5]. It is no doubt that safety and the environment will be a main area of interest for connected vehicle technology implementation.

Another area of interest and of main relevance to this study is in the realm of increased mobility. Connected vehicles impact mobility through the use of various systems including, but not limited to, automatic crash notification [6]; incident scene detection and alerts [7]; signal priority or reserved-lane priority for transit, emergency vehicle, and freight [8] [9]; adaptive signal control [10] and overall improvement of intersection efficiency [11]; dynamic transit operations [12]; and traveler information systems [13]. Others are attempting to detect spillbacks and adjust signal timing using connected vehicles in order to improve network throughput [14]. Many of these applications have the ability to replace current technologies with potentially more efficient implementations. As an example, connected vehicle technology makes dynamic routing possible with the consideration of real-time traffic status [15]. Vehicles then make a more informed choice about which route to take in order to minimize their own travel time, which balances transportation networks into a more realistic user equilibrium state, utilizing the entirety of the network.

Central to this paper is the use of connected vehicle for dynamic route guidance, where vehicles route through the network using ongoing, real-time information provided to them from other vehicles using connected vehicle technology. Dissemination of data is critical to vehicles being able to properly use the best routes. Although there are major challenges such as how to best broadcast messages, and dealing with security; work has been done to improve these areas [16]. In some cases, route guidance is proposed in order to solve a specific problem, such as congested off-ramps by diverting vehicles to other ramps to avoid ramp spillback [17]. Many others have sought to improve current route guidance methods by using prediction of the future state of a network [18] [19], while others have used fuzzy logic to aid the vehicle's decision-making [20].

Many multimodal methods of traveller information and route guidance systems have been researched. Researchers have analyzed the attributes that affect transit route choice as well as the decision to take transit [21], however these studies do not consider route choice through dynamic route guidance or connected vehicles. Tools have been developed that provide travellers with real-time transit information and use this to improve multi-modal trip planning [22] similar to how this study uses real time information for auto users. An advanced traveler information system has been proposed with multiple modes and a focus on pedestrians [23]. The concept of how best to use dynamic traffic assignment for short-term planning such as mode choice has been explored, aimed at presenting a framework for these situations [24]. By a the review of the literature, it is apparent that there is a great interest into route guidance as well as routing methods for multiple types of modes. However, how routing, and in particular dynamic route guidance, will effect mode choice, has yet to be studied. This paper is a start in bridging that gap by exploring how dynamic route guidance can affect mode choice and the performance of transportation networks.

2.4. Study Area

In order to evaluate the impact of dynamic route guidance available from connected vehicles on traveller mode choice, the connected vehicle was modeled in a microsimulation environment. The study area in question that was modeled is a part of the City of Toronto, Ontario network as shown in Figure 2.1. The study area includes the Toronto waterfront, bounded by Lake Ontario to the South, Dundas Street to the North, Woodbine Avenue to the East and Park Lawn Road to the West. The study area was developed, configured, calibrated, and validated by Abdulhai, et al. [25] in Paramics. The network was originally developed in order to study alternatives of how to best accommodate the Gardiner Expressway, an aging, grade-separated highway in Toronto. The microsimulation model reflects the study area in 2001 [26].

Figure 2.1: Study area [25]

The network was accurately modelled not only to study real-time metrics but also to allow for the creation of "a comprehensive simulation-based traffic management laboratory" which makes it adaptable and able to handle new situations, making it ideal for this study. The base road system was modeled using assistance from the City of Toronto's Digital Centerline data and then link categories, intersection geometry as well as turning movements were modified using multiple sources such as centerlines, photographs and site visits. Although transit lines and features can be modeled in Paramics, they were considered beyond the scope of the initial network development.

The network contains 1825 nodes in total, 227 of which are signalized; some using an actuated signal plans using loop detectors. There are 4012 links in total; 129 highway links, mainly the Gardiner expressway, and 3883 urban links. The Gardiner Expressway is a main feature of the network. It is a major highway with a speed limit of 90 km/hr, three lanes in each direction, running along the south of the city. Links were developed using 62 separate link categories. The average travel time of the network during peak hours is 8.53 min, with an average speed of 43.4 km/hr. Depending on the location of the count, during the AM peak, volumes along the Gardiner Expressway are approximately 4500 veh/hr in the westbound direction and 3000 veh/hr in the eastbound direction.

Demand estimates were created using a three step procedure based on data from the Transportation Tomorrow Survey (TTS), a telephone survey done every 5 years in the Greater Toronto and Hamilton Area sampling 5% of the population. The survey collects personal data such as income and traveller information such as place of work. Traveller and trip characteristics can be extrapolated from this data. A static traffic assignment was performed in the macrosimulator EMME/2 for the entirety of the Greater Toronto Area. The Toronto waterfront portion was then analyzed to ensure that the level of traffic was consistent with real world conditions. As part of this, the speed and capacity of many links were adjusted until reasonably consistent conditions were met. The assignments from this model were then used to develop seed origin-destination demands for the study.

Actuated signals were modeled using the Paramics plan language by receiving information from detectors that are coded into the network. These detectors provide the information needed to run the algorithms. Many intersections in this area of Toronto are manually optimized to reflect real traffic conditions contain transit signal priority, or are adaptive cycles. These were not modeled due to a variety of reasons such as time constraints and inability to recreate changes in the timing. Modeled timing algorithms were created in order to reflect minimum green times from pedestrian movements and flows registered by loop detectors. Modifications were then made to intersections with special phases such as advanced turns.

Some small network parameters were adjusted in order for the network to properly meet the needs of the study. At certain external zones, demand was seen to be queuing outside of the network. As such, when network performance was improved, more vehicles were released into the network, thereby deteriorating performance of the network. Therefore, the demand at these points was reduced to equal the flow entering the network. This ensures that the performance of the network remained unchanged but further vehicles were released under improved different conditions.

2.5. Methodology

2.5.1. Overview of Methodology

An iterative process is proposed to evaluate the impact of connected vehicle on the mode share of auto, transit, cycling and walking. A flow chart of the methodology is shown in Figure 2.2. The methodology is mainly comprised of two parts. The mode choice model produces the share associated with all modes available for a given origin-destination pair based on an initial travel time; considering auto, transit, cycling and walking. The initial travel times reflect the travel times of the study area with no connected vehicles. Demands for all modes are taken from the TTS. A vehicle assignment is then performed using a given market penetration of connected vehicles and new average travel times are determined. Market penetration refers to the percentage of vehicles that are equipped with connected vehicle technology. The newly estimated average travel times are then utilized to determine the new mode shares. This process continues until the algorithm converges and the travel times will not cause a change in mode choice. The process is iterative because travel times will affect the mode choice of users and the mode choice impacts the demand for auto which changes the travel times. The main components of Figure 2.2 are described below.

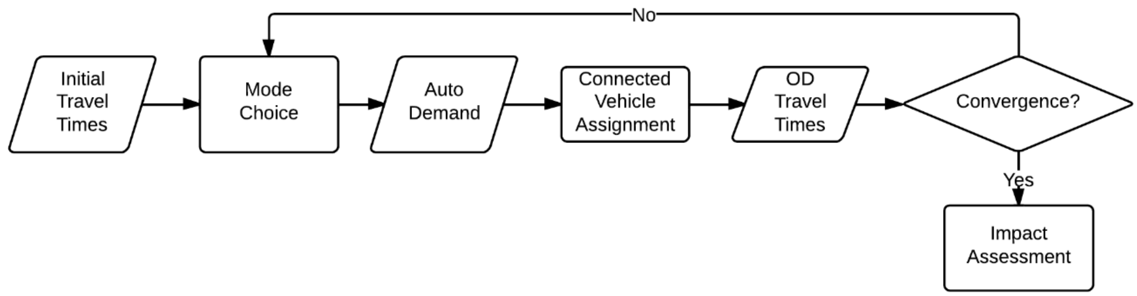

Figure 2.2: Flow chart of the proposed methodology

2.5.1.1. Mode Choice

The mode choice component of the proposed methodology includes a multinomial logit model which was developed as part of this research using data from the City of Toronto. Average trip travel time is the main independent variable in the utility functions of the logit model. These models are used to capture the change in mode shares due to change in average travel time for a given Origin-Destination (OD) pair.

2.5.1.2. Connected Vehicle Assignment

An application programming interface (API) has been developed for Paramics in order to model connected vehicles [27]. For the purposes of this study, V2V communications was modeled with a focus on dynamic route guidance. This assumes that vehicles are communicating to each other without the aid of infrastructure. Dynamic route guidance is technology that allows the updating of route choice information, which is changeable throughout the trip; based upon real-time V2V-enabled information. In essence, a route-guidance system is updated with real time information from other vehicles which changes routes based on the best current travel times.

The API has V2V-enabled vehicles keep a table of the times they have taken to traverse each link in the network. When a vehicle chooses its route, it checks to see which vehicles are within a user-defined range and chooses the most recent link times from these vehicles to update its own table. Vehicles only store the most recent information they have from other vehicles. The range is designed to comply with the Dedicated Short-Range Communication (DSRC) technology and is set at a distance of 1000 meters for this study.

The range can be changed to meet the real reach of various types of communication technology. The vehicles then use these tables to choose the quickest path to their destination. This continues during the simulation with the tables being updated at a user-defined interval, chosen for this study as 2 minutes. The interval must be small enough to be practically real-time but can also be very computationally intensive so a balance must be reached. For this study, the assumption is made that all connected vehicles will always follow the quickest path given to them by their trip table. This differs from the standard vehicle assignment as vehicles update their information in real-time using the most recent available information. Connected vehicles also have the ability to predict the travel time for the entire route and not just the next few steps for the vehicle.

2.5.1.3. Convergence

As the iterations are run, the system will move to a state where all users are satisfied with their choice. In this state, the travel times will not cause a change in mode choice. This convergence is said to be reached for this paper when the change in average travel times of all trips in the network is less than 5% from the previous iteration, as used in other studies [28].

2.5.1.4. Impact Assessment

The results will be assessed in order to gauge the change in travel times both from the introduction of connected vehicles directly, as well as the new travel times due to the resultant change in mode choice. The change in mode choice is also assessed in this phase. Various market penetrations of connected vehicles are considered in the impact assessment.

2.5.2. Choice Model Development

A logit model is used in this study in order to determine mode choice. A logit model is a choice model with the concept that each individual in the model attempts to maximize their utility, given by Equation 2.1.

$$V_i = \beta_{0,i} + \beta_{1,i}x_{1,i} + \beta_{2,i}x_{2,i} + \cdots + \beta_{N,i}x_{N,i} \qquad \text{Eq. 2.1}$$

where,

V_i is the utility for mode i, $\forall i = 1, \cdots, M$

$x_{j,i}$ denotes independent variable j for the utility function for mode i, $\forall j = 1, \cdots, N$

$\beta_{j,i}$ are the coefficients for each variable $x_{j,i}$ $\forall j = 1, \cdots, N$

In order to find the probability that an individual will use one mode over the others, Equation 2.2 is used.

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{M} e^{V_j}} \qquad \text{Eq. 2.2}$$

In this equation, P_i is the probability of an individual choosing mode i and M is the number of available modes.

Key decisions in the development of the logit model included the choice of modes to use and the utility function parameters. All data for the model development was taken from the TTS 2001 survey. The modes used in the model are auto drive, transit, cycle and walk modes. Although the use of non-motorized modes in a logit model is somewhat novel, it was considered necessary due to the fact that non-motorized modes account for 70% of the trips in the study area. It is plausible that the change in auto travel times could impact the share in non-motorized modes.

There are two general types of variables that can be used for function parameters; alternative specific and generic variables. Alternative specific variables are characteristics of the individual road users which may have a different coefficient for each mode. An example of this would be number of vehicles in the household or income level. For the trip maker, the values are the same regardless of mode but the relationship with the utility is different for each mode. Generic variables, on the other hand, are characteristics of the alternative modes and will have the same coefficient for all modes. An example of this could be in-vehicle travel time where the user experiences a different value for each mode but perceives the utility of the variable equally across modes. The variables considered in this study are travel time, number of vehicles in household and driver's license which are known variables to be tied to mode choice. Driver's license was not used as they produced a singular system, meaning there was not enough variance in the variable to produce a relationship. This makes sense as there can be only two possible values; a user possessing or not possessing a driver's license.

Travel times for the different modes were gathered in different formats. Auto travel times were taken from running the Waterfront microsimulation model and taking the average travel time between each internal zone for regular passenger vehicles. Each individual was assigned the average travel time of the zones they were traveling between. Transit times were gathered using an EMME model by running a transit assignment. Transit lines consisting of bus, streetcar and subway were modelled using information from the Toronto Transit Commission's website [29] in order to determine stop locations, headways and other necessary information. Transit demands were taken from the TTS and assigned to the model using the origin and destination of each trip as the centre of each TTS zone. Transit assignment parameters are shown in Table 2.1 along with the definition of each parameter.

Table 2.1: Transit assignment parameters [30]

Parameter	Value	Meaning
Walk speed	4.0	Walk speed to or from transit in km/h
Walk time weight	2	Traveller's value of walk time in comparison to in-vehicle travel time
Wait time factor	0.5	Distribution of traveller's arrival to transit stops. 0.5 assumes arrival at random.
Wait time weight	2	Traveller's value of wait time in comparison to in-vehicle travel time.
Boarding time weight	1	Traveller's value of boarding time in comparison to in-vehicle travel time.
Boarding time penalty		Additional time for boarding, applied to each mode separately in minutes.
Bus	2	
Streetcar	2	
Subway	0	

The travel time variable was modified a few times, as described below, in order to produce accurate results. Initially in-vehicle travel time was used for motorized modes and distance was used for the non-motorized modes. In addition, wait and walk times were added for the transit mode. These results can be seen in Table 2.2, showing that in-vehicle travel time had a positive coefficient, meaning that a higher travel time would cause an individual to be more likely to use a mode, an impractical situation. Next, distance was removed from the non-motorized modes and replaced with travel times using the distance and an assumed average speed of 15 km/h for cycling and 4 km/h for walk. A similar problem resulted, indicating that it was likely that transit times were causing the discrepancy since transit is the only mode not taking into account the total trip time. For transit; in-vehicle travel time, wait and walk times were combined so that each mode has the same overall travel time measure, therefore a generic variable was used which generated appropriate results. It should be noted that this assumed that the trip-maker perceives in-vehicle travel time the same as wait and walk times as well as across modes, having one “door-to-door” travel time for all modes. This was done in order to properly incorporate the cycle and walk modes. The model parameters can be seen in Table 2.3. It should be noted that all values are statistically significant.

Table 2.2: Initial, unused logit model parameters

Coefficients	Type	Mode	Estimate	P-Value
Intercept	Alternative Specific	Transit	-1.015	$< 2.2X10^{-16}$
Intercept	Alternative Specific	Non-motorized	1.1676	$< 2.2X10^{-16}$
In-vehicle time	Generic		0.0023122	$< 2.2X10^{-16}$
Wait time	Generic		-0.0019198	$1.295X10^{-13}$
Walk time	Generic		-0.0006336	$4.891X10^{-7}$

Table 2.3: Logit model parameters

Coefficients	Type	Mode	Estimate	P-Value
Intercept	Alternative Specific	Transit	3.2273	$< 2.2\text{X}10^{-16}$
Intercept	Alternative Specific	Cycle	0.22362	0.004644
Intercept	Alternative Specific	Walk	4.6405	$< 2.2\text{X}10^{-16}$
Travel Time (seconds)	Generic		-0.1014446	$< 2.2\text{X}10^{-16}$
Vehicles in Household	Alternative Specific	Transit	-2.1405	$< 2.2\text{X}10^{-16}$
Vehicles in Household	Alternative Specific	Cycle	-1.7267	$< 2.2\text{X}10^{-16}$
Vehicles in Household	Alternative Specific	Walk	-2.3032	$< 2.2\text{X}10^{-16}$

The McFadden R^2 is used to assess the significance of the model, which takes the form seen in Equation 2.3.

$$R^2 = 1 - \frac{\ln L(M_{full})}{\ln L(M_{intercept})} \qquad \text{Eq. 2.3}$$

$L(x)$ is defined as the likelihood of a model x. The likelihood of a model is a measure of how likely the model is to predict the correct result. M_{full} represents the full model developed for this study and $M_{intercept}$ is an equivalent model just involving the intercept. The two models allow for an exploration into how much of a predictive capability the chosen variables have. Therefore, the McFadden R^2 is a measure of how much more of a predictive capability the parameters are providing. For the given model, the McFadden R^2 value is 0.25586.

The likelihood ratio test is used to determine if the full model has a significantly better fit than the model with just the intercept, which is testing the null hypothesis that the two models are statistically the same. In this case, the p-value is less than $2.2\text{X}10^{-16}$, significantly less than 0.05, meaning that the two models are statistically different at a 95% confidence interval. One can then infer that the variables chosen have a predictive capability in the model.

In addition, a sensitivity analysis was performed on travel time to gauge the impact on mode share. This was done using an aggregate direct elasticity which indicates the weighted average of the individual (k) elasticity for a specific subgroup of N for mode i, in our case for all auto users. The result is found using Equation 2.4 for the individual elasticity and Equation 2.5 for aggregate direct elasticities.

$$E_k = (1 - P_{ki})x_k\beta_i \qquad \text{Eq. 2.4}$$

$$E = \frac{\sum_{n=1}^{N} P_{ki}E_k}{\sum_{n=1}^{N} P_{ki}} \qquad \text{Eq. 2.5}$$

where,

E is the elasticity,

P_{ki} is the probability,

x_k is the value of the variable for the individual,

β_i is the utility coefficient for mode i.

For use in this study, Equation 2.3 indicates the weighted elasticity of auto drivers to changes in travel time. Results show the elasticity as -0.5309, indicating that for every minute increase in auto travel time, an individual will be 0.5309% less likely to use the auto mode.

To provide the most accurate results possible, the market penetration not only represents the percentage of connected vehicles in the simulation, but also the percentage of the population that has access to connected vehicles in general if they were to switch. This is an important distinction as the connected vehicles and regular vehicles will likely have different travel times due to the difference in routing. Therefore each population is considered separate, the mode choices calculated separately, and the demands are combined to find the total demand.

2.6. Results

2.6.1. Travel Time

In order to analyze travel time, the average travel time for all vehicles is used for the various market penetrations of connected vehicle as it is directly correlated to network mobility and mode choice. This analysis is performed for the initial run, representing the performance of the network without considering traveller's change in mode, and then for the final run after convergence, representing the state of the network after the consideration of mode choice. These results are shown in Figure 2.3 with CV representing the connected vehicles, Others representing non-connected trips, and total representing all vehicles. Note that for 0% market penetration there are no connected vehicles, and therefore, only others and total are shown. The same occurs at 100% market penetration, as there are only connected vehicles at this point. A t-test was performed for each market penetration's average travel time, in order to determine if it was significantly different from the base case at 0%. The results are shown in Table 2.4.

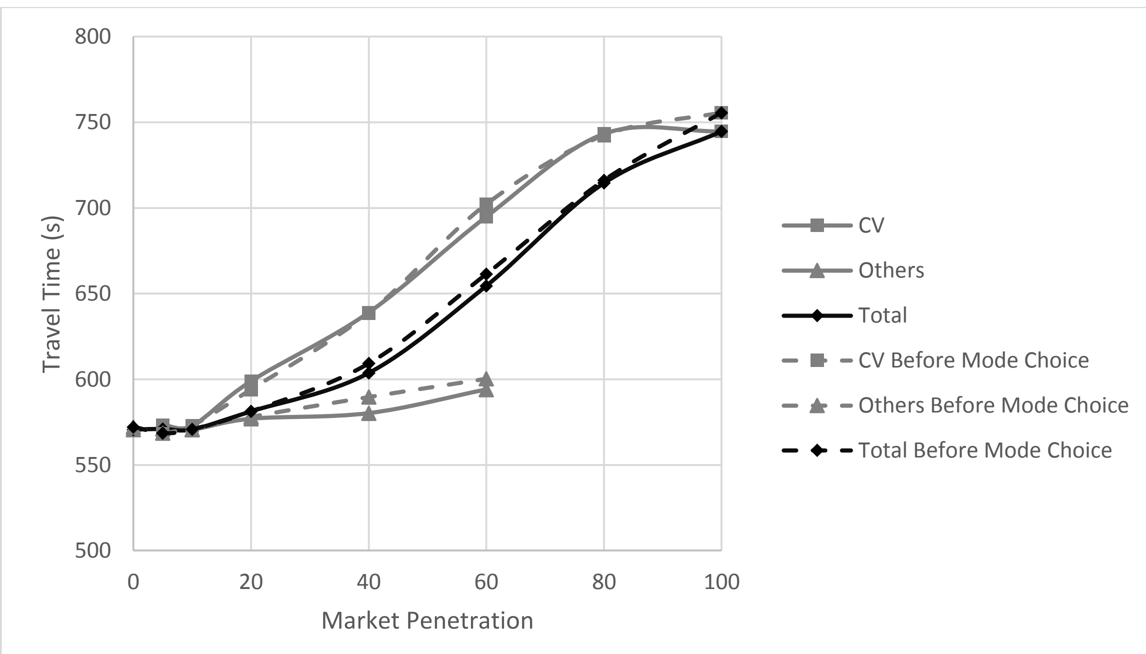

Figure 2.3: Average network travel time before and after the consideration of change in mode choice

Table 2.4: Travel time average significance by t-test

Market Penetration (%)	P-value	Significant for 95% confidence interval?
5	0.9113	No
10	0.8343	No
20	0.1025	No
40	0.0004	Yes
60	0.0005	Yes
80	< 0.0001	Yes
100	< 0.0001	Yes

The results show that, although the presence of connected vehicles may initially reduce travel times, they inevitably increase travel times proportional to market penetration. This increase is significant for market penetrations of 40% and 100%. Other studies have presented similar results. The concept of selfish routing is embedded in this route guidance scheme, which has been shown to significantly increase delays [31]. One possible reason is the suggestion of the same path to too many drivers, with researchers proposing new routing algorithms to overcome this [32]. Others have attempted to suggest a more reliable route guidance system [33]. Additional test scenarios were performed to study the observed results in travel time increase. In order to determine the contributing factor to the increase in travel time, test networks in Paramics were set up and different factors were varied. These factors are:

- Network complexity,
- Number of lanes,
- Demand level, and
- Connected vehicle market penetration.

The networks used are shown in Figure 2.4 in increasing orders of complexity. The side roads were analyzed with 1 and 2 lanes for each scenario; however since there was no significant difference between the two cases, only the 1-lane scenario is shown here.

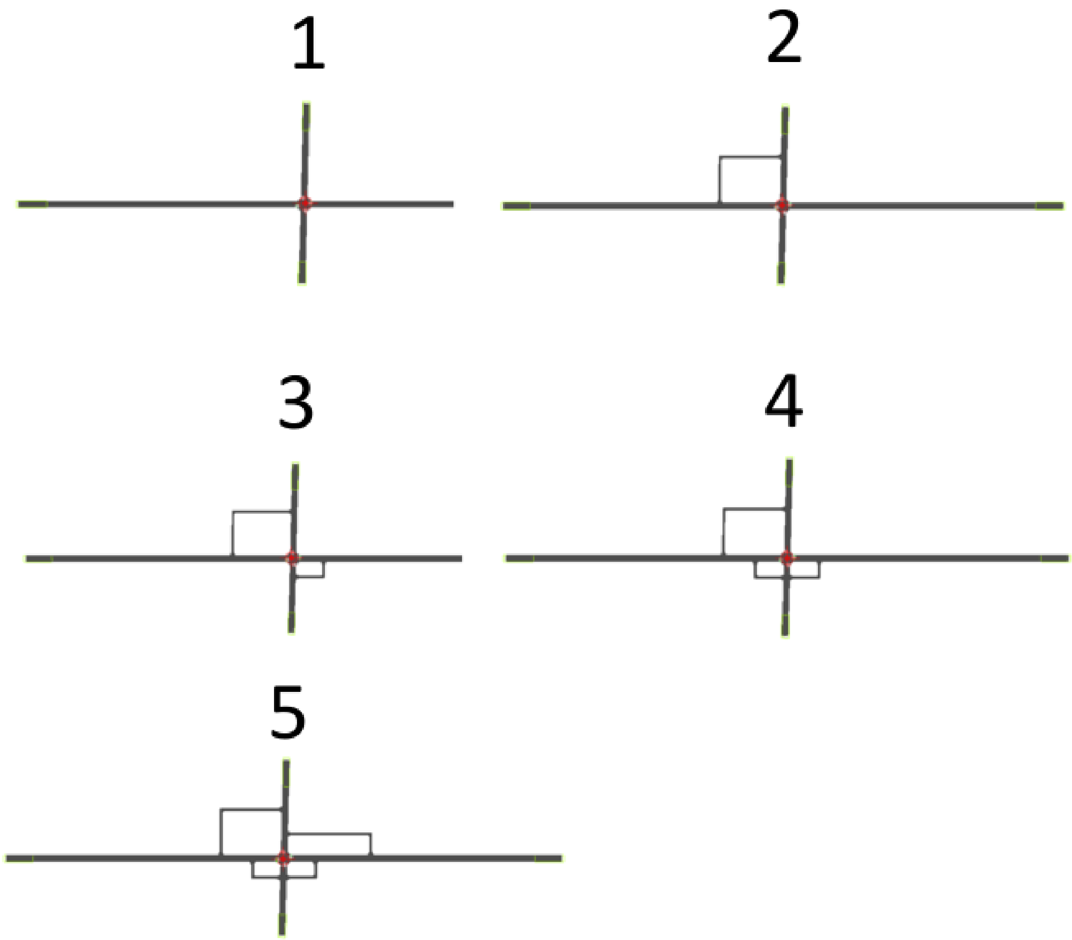

Figure 2.4: Test networks in order of complexity from 1 to 5

The flow throughout the network is shown in Figure 2.5 for various market penetrations of connected vehicles, with each graph representing each corresponding test network. It should be noted that flow was used by measuring how many vehicles were able to make it through the network in one hour instead of travel times as travel times were unreliable at levels of high congestion. Under these high congestion situations, not many vehicles were able to make it through the network.

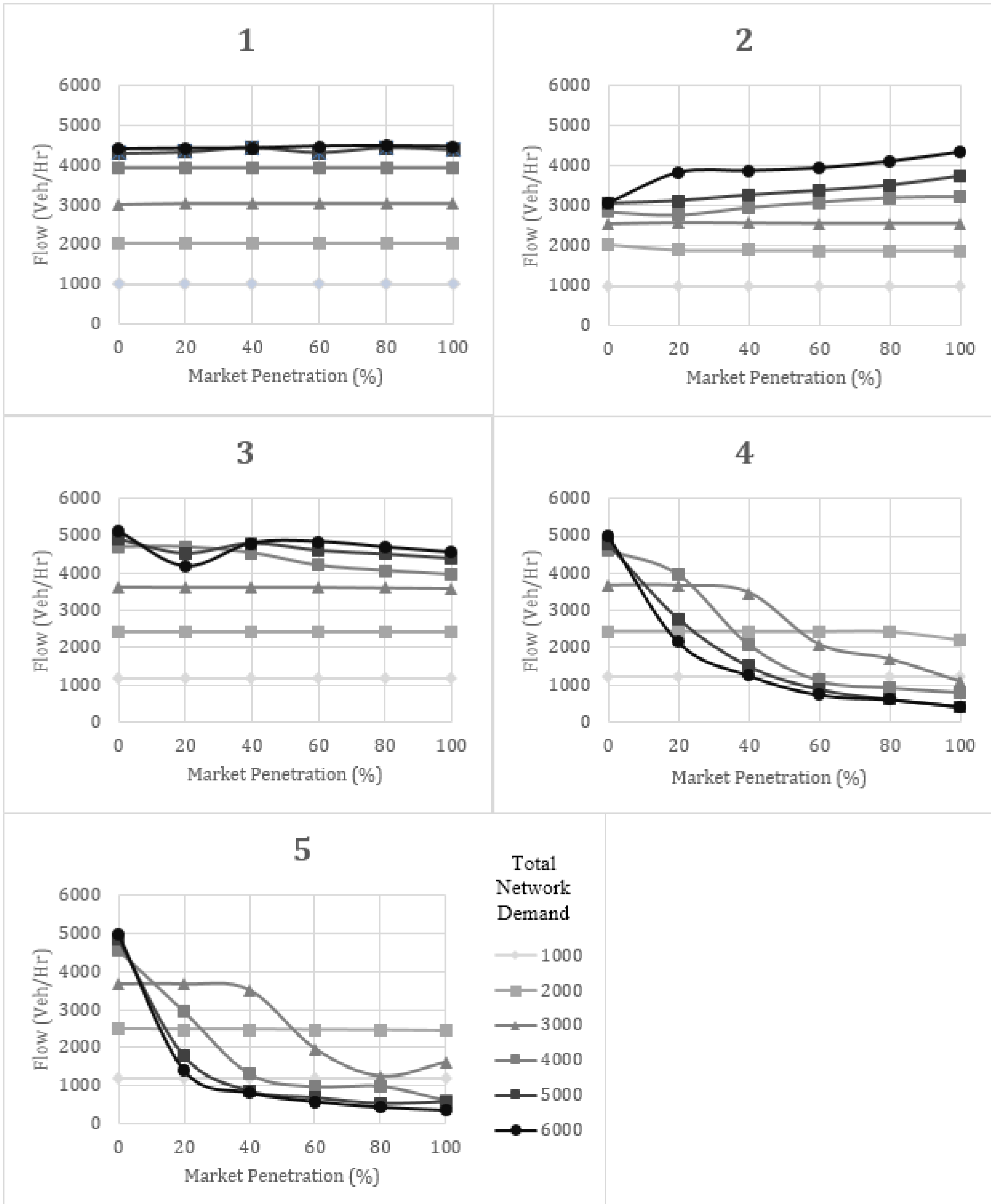

Figure 2.5: Network flow given market penetrations of increasing demand and network complexity

It can be observed that in a complex network, at high levels of demand and high market penetrations, the flow of the network drops significantly, often even dropping below values of lower levels of demand at the same market penetration. Therefore, the reduced travel times seen in the main Toronto waterfront network can be attributed to this phenomenon. The phenomenon is believed to be created by quick movement of vehicles to and from different routes. As many vehicles reroute to a path with a lower capacity, they do so before vehicles are able to set new link times and communicate them back. These new paths are not able to accommodate the new demand and thus, become congested. The dynamic route guidance algorithm does not take into account future travel times and, as such, conditions can change by the time the vehicles reach their new route.

2.6.2. Mode Choice

The total mode choice for each market penetration analyzed can be seen in Figure 6.

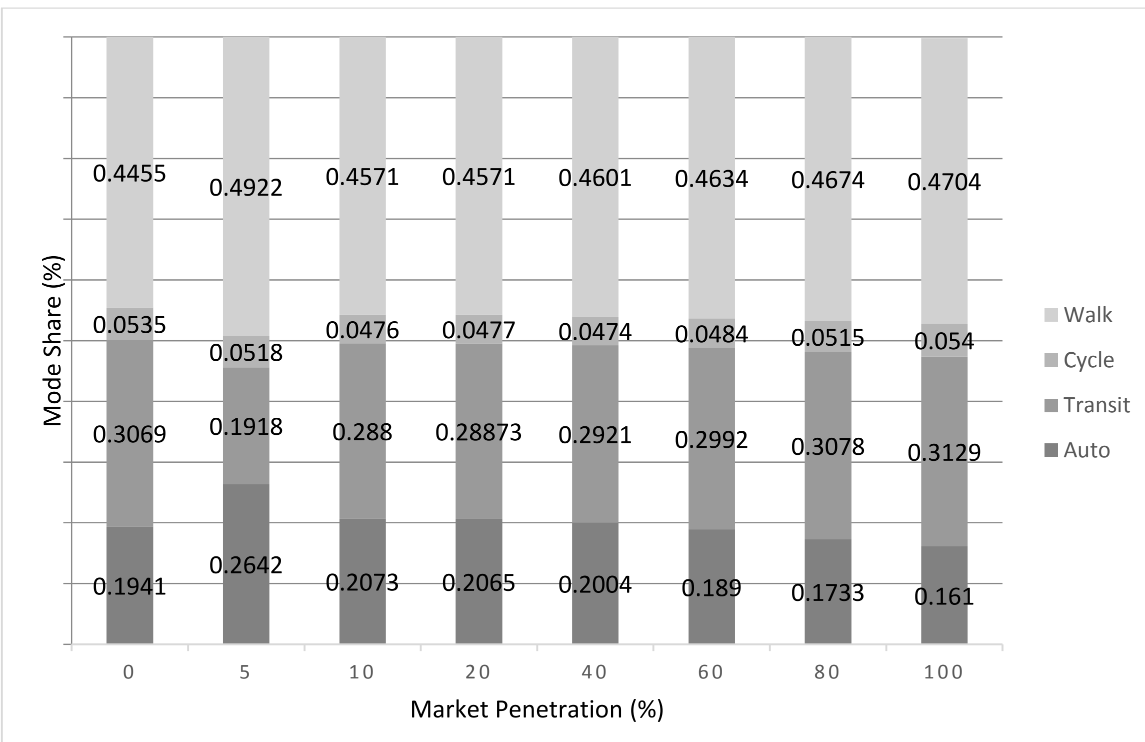

Figure 2.6: Mode share for various market penetrations of connected vehicles

Mode share does not change for the majority of market penetrations. In these cases, we can conclude that the introduction of connected vehicles do not change the performance of the network enough to influence a change in mode choice. However, there are exceptions. The first is at a 5% market penetration where the introduction of connected vehicles caused a reduction in travel time. In this case, the auto share increases by approximately 7%, while transit share decreases by 11.5% and walk share increased by 4.5%. This may show that the model is sensitive to decreases in travel as opposed to increases but these results should be taken lightly as this travel time was not statistically significant from the 0% case. The other exception is for high market penetrations. For example, at 100% market penetration, auto share decreases by 13.3% and is replaced by all the other modes. This makes sense as the increase in travel times will push users to other modes.

2.7. Conclusion

In order to properly understand the effect that a new technology, such as connected vehicles, can have on a transportation network it is imperative to examine the potential consequences. This paper explores the effect on mobility and mode choice. Although the direct effect of the technology has been studied, this paper studied this impact on system demand in a large scale simulation environment. Examining the effects of connected vehicle on mode choice provides more detailed insight into the performance of the network as well as changes in demand of various modes. The results show that travel times will increase for high market penetrations if a dynamic route guidance algorithm, as proposed in this paper, is implemented. The results show a move away from the auto mode for high market penetrations. This information can aid decision-makers in planning how to account for connected vehicles and guide developers of connected vehicle technologies.

2.8. Acknowledgments

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3. Conclusions

This research highlights the importance of evaluating new transportation technologies on the performance of transportation networks. In addition, taking into account changes in demand on the system provides a more accurate and informative view of the transportation landscape. Connected vehicles have the capability to change the transportation landscape in a number of ways, and it is advantageous to all parties involved to have an understanding of the positive and negative consequences in terms of network performance and mode choice. The results show that for large market penetrations of connected vehicle, travel time of the network increases, caused by features of the network. These include high network complexity, market penetration and demand. Mode choice saw a decrease in the auto share due to the increase in travel times and increase in transit, cycling and walking.

One further area of exploration is the behaviour of the mode shares, shown in Figure 2.6. A 5% market penetration results in a very large increase in the auto share even though the change in average travel time was very low, seen in Figure 2.3. In contrast, higher market penetrations exhibit a much larger increase in average travel time but show a very modest decrease in mode choice. One possible reason is that the original size of the auto share too low so show a large decrease. In order to better understand this, we can use a hypothetical example of a two-mode system, shown in Figure 3.1. On this curve, this auto example could be represented by a low choice probability in the bottom-right. A change in utility to the right of this location would only show a modest decrease in choice probability, while a change to the left will result in a much larger increase in probability. The logit model used in this study is exhibiting similar behaviour in terms of how the auto mode is reacting to changes in travel time. This indicates an interesting characteristic of the study area. Specifically, that the majority of travellers that are influenced by travel time have chosen to use non-auto modes due to the large travel time cost associated with it. The current auto users are not sensitive to travel time and derive all their utility elsewhere, or are captive to the mode. This causes the majority of them to not change modes even for large increases of travel time. This is consistent with the results shown, as the study area is heavily congested during the period studied and it is possible that most auto users could find a smaller travel time with a different mode.

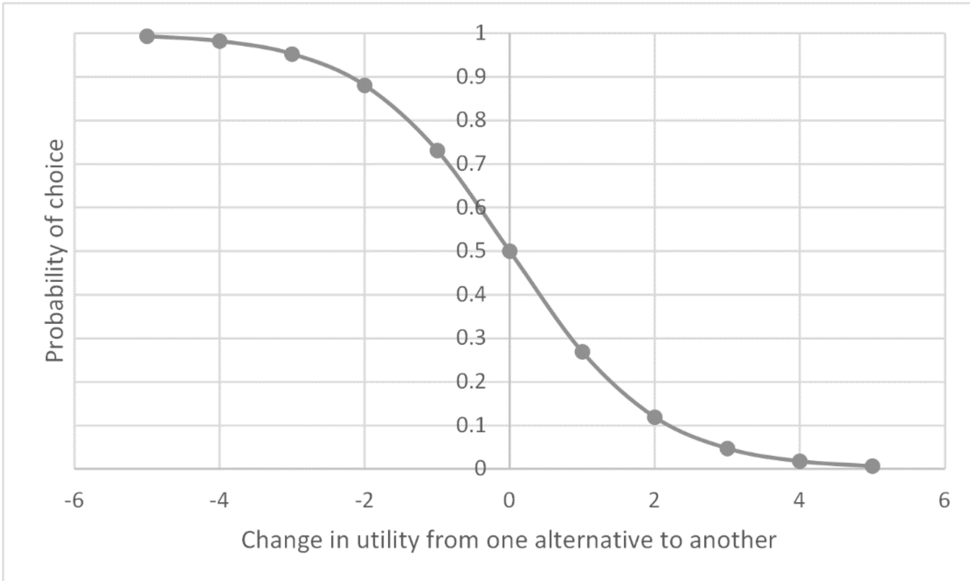

Figure 3.1: Hypothetical probabilities for a two-alternative system

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