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Evaluation of connected vehicle impact on mobility and mode choice

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ABSTRACT

Connected vehicle is emerging as a solution to exacerbating congestion problems in urban areas. It is important to 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 demands for various modes were modified based on the changes in travel time between each origin-destination (OD) pair caused by introduction of connected vehicle. Then a traffic assignment was performed in a micro-simulation model, which was 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, Canada. 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 the whole auto mode will generally increase, with the largest increase from connected vehicles. This causes an overall move away from the auto mode for high market penetrations if a dynamic route guidance algorithm is implemented.

1. Introduction

A vehicular ad hoc network (VANET) uses vehicles as communication points in order to create a wireless network. The connected vehicle (CV) 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

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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 (Genders and Razavi, 2015; Olia et al., 2015). 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 travelers 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 on mode choice will be studied throughout this paper.

Understanding the impact that dynamic mobility 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. 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 technology including latency, communication range, and market penetration (MP) (Dion et al., 2011).

Areas of application include, but are not limited to, safety, mobility, and environmental sustainability. An area of interest with main relevance to this study is in the realm of increased mobility. Connected vehicles impact mobility through the use of various systems including incident scene detection and alerts (Zhuang et al., 2011), signal priority or reserved-lane priority for transit, emergency vehicle, and freight (Wang et al., 2014), adaptive signals (Feng et al., 2015), ramp metering (Kattan and Saidi, 2013), overall improvement of intersection efficiency (Guler et al., 2014), and strategies to detect and deal with queue spillback (Li et al., 2013). Aside from the auto mode, transit is also a large focus of connected vehicle, including bus operations optimized for signal timings (Ma et al., 2013), dynamic transit operations (He et al., 2011), and various other applications (Huff et al., 2015). Some are even exploring new modes of transportation such as a fleet of deployed vehicles that respond to travelers in real-time (Jung et al., 2015). Others are attempting to detect spillbacks and to adjust signal timing using connected vehicles in order to improve network throughput (Rivadeneyra et al., 2014). 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 (Ding et al., 2010). 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. Vehicles route through the network using ongoing and real-time information provided to them from other vehicles. This is facilitated through connected vehicle technology. Dissemination of data is critical to vehicles being able to properly use the best routes. In some cases, they can provide travelers with personalized routes, based upon user preferences (Ma et al., 2015). Although there are major challenges such as how to best broadcast messages and deal with security, work has been done to improve these areas (Chen et al., 2011). 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 (Spiliopoulou et al., 2014). Many others have sought to improve current route guidance methods by using prediction of future state of a network (Park et al., 2010; Xu et al., 2011), while some are looking at the impact of accurate information (Ben-Elia et al., 2013).

Many multimodal methods of traveler 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 (Eluru et al., 2012). However, these studies do not consider route choice through dynamic route guidance or connected vehicles. Tools have been developed that provided travelers with real-time transit information and used this to improve multi-modal trip planning (Zhang et al., 2011) 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 (Yu and Lu, 2012). The concept of how to use dynamic traffic assignment best for short-term planning such as mode choice has been explored, aimed at presenting a framework for these situations (Sundaram et al., 2011). By a 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 not 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.

3. Proposed method

3.1. *Overview of proposed method*

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 Fig. 1.

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 survey data, as discussed later in this paper. 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 which 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 do 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 Fig. 1 are described below.

3.2. *Mode choice*

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 Eq. (1)

$$V_i = \beta_{0,i} + \beta_{1,i}x_{1,i} + \beta_{2,i}x_{2,i} + \cdots + \beta_{N,i}x_{N,i} \tag{1}$$

where V_i is the utility for mode i, $i = 1, \cdots, M$, $x_{j,i}$ denotes the independent variable j for the utility function for mode i, $\beta_{j,i}$ is the coefficient for each variable $x_{j,i}$, $j = 1, \cdots, N$.

In order to find the probability that an individual will use one mode over the others, Eq. (2) is used

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{M} e^{V_j}} \tag{2}$$

where P_i is the probability of an individual choosing mode i, M is the number of available 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 from 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 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. Further development of this model is expanded upon later in this paper. It should be noted that the market penetration is treated as the percent of the population who has access to a connected vehicle. Therefore, the population is split by market penetration and each is run through the mode choice model using their respective travel time. This essentially assumes that the market penetration also represents the percentage of the population that have connected vehicles accessible to them. Mode choice models then run for the percentage of the population who has access to connected vehicles and run for the percentage of the population who has not, based upon the respective vehicle's performance. Each one provides a new modal split between vehicles (connected or not), transit, cycling, and walking. A flow chart of this process can be seen in Fig. 2.

3.3. *Traffic assignment*

Traffic assignment was performed using a microsimulation environment. The assignments of connected and non-connected vehicles were treated differently as to incorporate their unique characteristics. Each mimicked traffic conditions of a typical weekday between the hours of 8 and 9 AM. Each iteration ran a total of 6 simulations runs that were then averaged in order to normalize the results and to produce a more typical day.

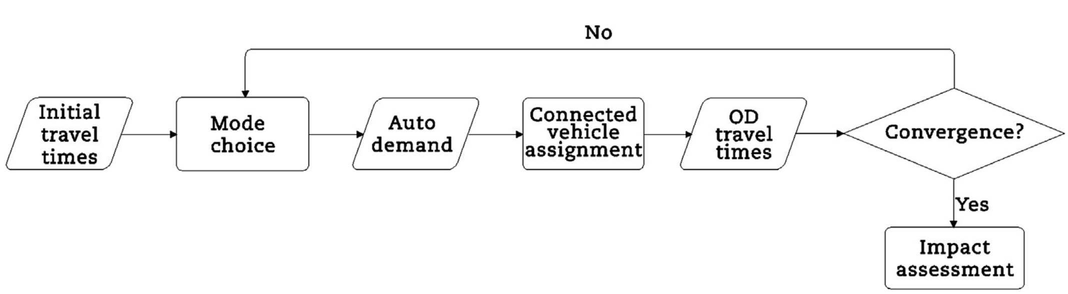

Fig. 1 – Flow chart of proposed methodology.

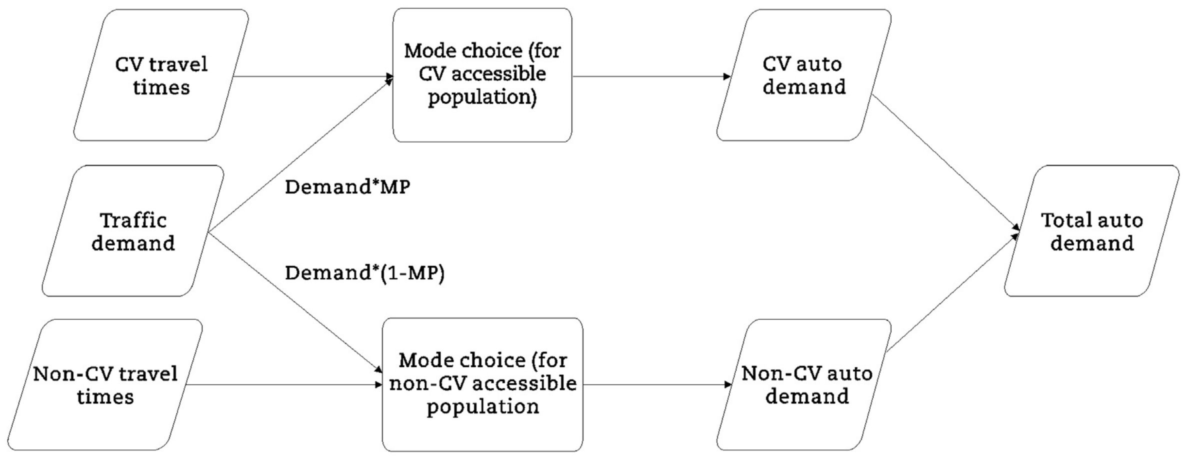

Fig. 2 – Flow chart of mode choice process.

3.3.1. *Paramics traffic assignment for non-connected vehicles*

Quadstone Paramics is a traffic microsimulator that simulates each agent vehicle individually for the purpose of traversing traffic networks. 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 to get its destination. It should be noted that vehicles do not prepare a route for their entire destination, rather, only for a few next steps. There is a crucial difference between regular vehicle assignment and connected vehicle assignment. The cost is taken as a user-defined mix of time, distance, and tolls, but this study takes the cost as just time.

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 needed. 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 to have access to updated table costs. While unfamiliar vehicles do not have updated information available, therefore, use a predefined route. In addition, Paramics introduces a degree of randomness into the perceived costs that the vehicles have in their cost tables. It should be noted that all non-connected vehicles will use this type of Paramics routing for this study.

3.3.2. *Traffic assignment for connected vehicles*

An application programming interface (API) has been developed for Paramics in order to model connected vehicles (Olia et al., 2013). For the purposes of this study, V2V communications are 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 a 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 cost table similar to Paramics. This is initialized using the length and speed limit of each think. As vehicles traverse the network they update the table using the time they took to traverse a link. When a vehicle chooses its route, it checks which vehicles are within a user-defined range and receives the most recent link times from these vehicles to update their own table. Since we are modeling V2V only, travel times are only communicated between connected vehicles and not through some central points. Vehicles only store the most recent information which they get 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 m 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, which is chosen as 2 min for this study. The interval must be small enough to be practically in 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, not just the next few steps for the vehicle.

3.4. *Convergence*

As the iterations 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 (Izadpanah and Aashtiani, 2012).

3.5. *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 travel times for the market penetrations studied will be presented in order to assess changes and trends that connected vehicles introduce. The change in mode choice is also assessed in this phase. Changes in this area show a large impact on the transportation landscape. Various market penetrations of connected vehicles are considered in the impact assessment. A graphical representation is shown in Fig. 3.

4. Hypothetical test network

In order to determine the contributing factors to the unexpected 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
- Connected vehicle market penetration

The networks used are shown in Fig. 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. The flow throughout the network is shown in Fig. 5 for various market penetrations of connected vehicles, with each graph representing the 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.

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 below the 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.

5. Study area

The study area in the question that was modeled is a part of the City of Toronto, Ontario network as shown in Fig. 6. 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

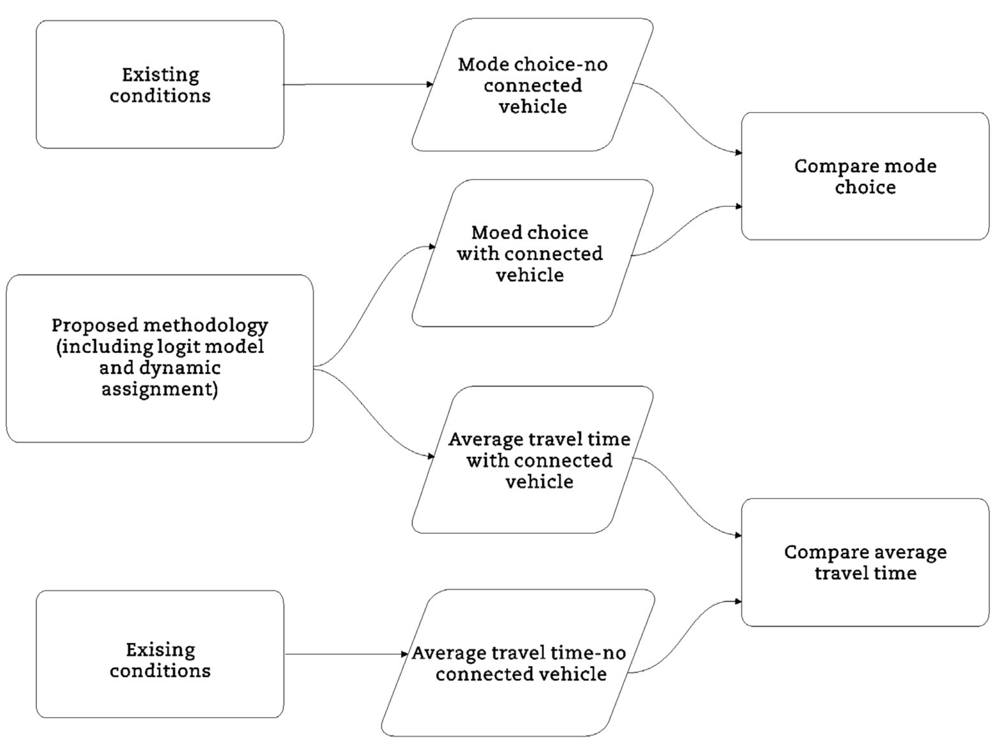

Fig. 3 – Flow chart of impact assessment process.

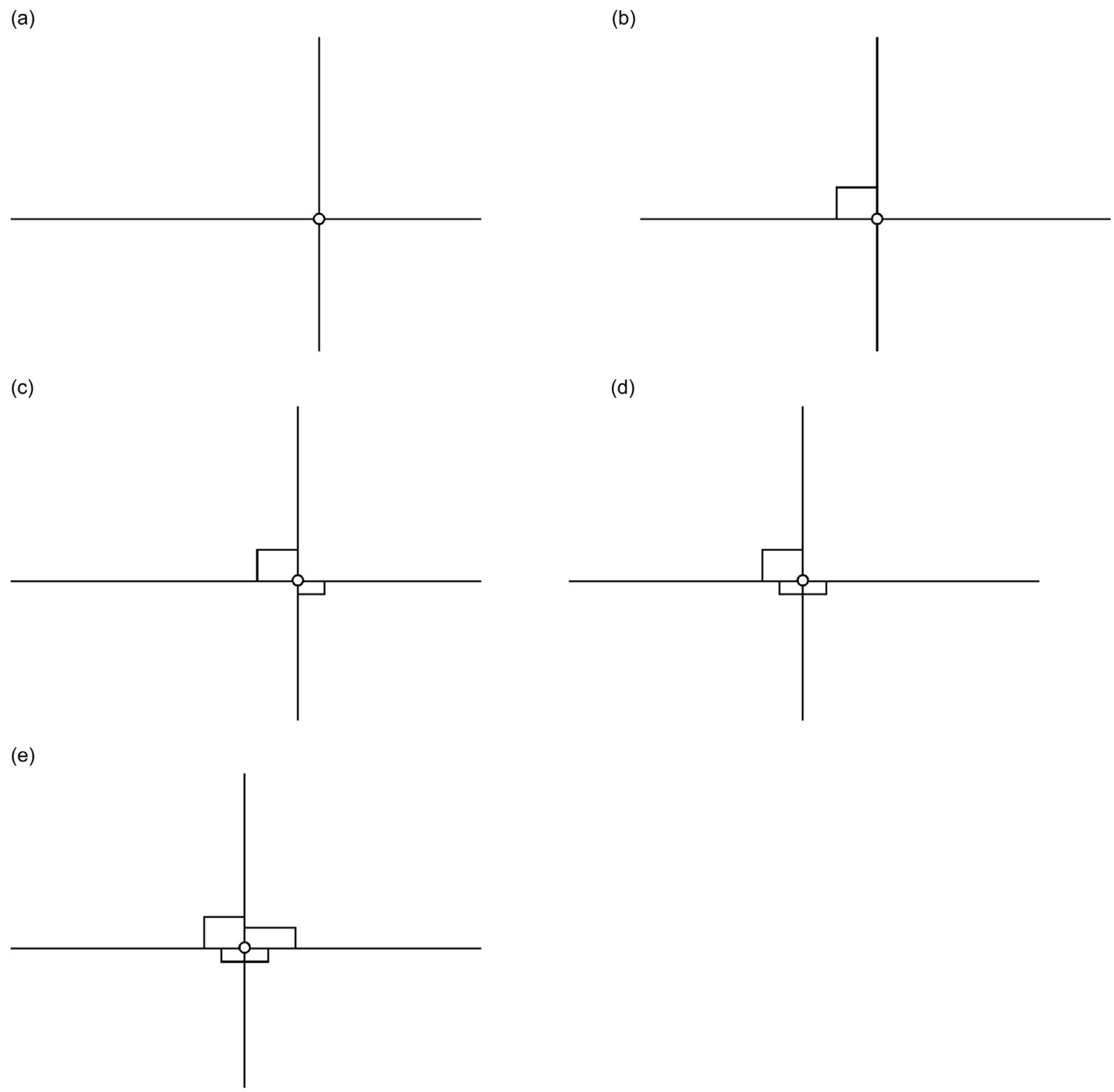

Fig. 4 – Test networks in order of complexity from 1 to 5. (a) Network 1. (b) Network 2. (c) Network 3. (d) Network 4. (e) Network 5.

West. The Gardiner Expressway is a main feature of the network. It is a major highway with a speed limit of 90 km/h, 3 lanes in each direction, running along the south of the city. The average travel time of the network during peak hours is 8.53 min, with an average speed of 43.4 km/h. Depending on the location of the count, during the AM peak, volumes along the Gardiner Expressway are approximately 4500 veh/h in the westbound direction and 3000 veh/h in the eastbound direction.

6. Paramics model development and calibration

In order to evaluate the impact of dynamic route guidance available from connected vehicles on traveler mode choice, the connected vehicle was modeled in a microsimulation environment. The study area was developed, configured, calibrated, and validated by Abdulhai et al. (2002) 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 (Amirjamshidi and Roorda, 2011) and can be seen in Fig. 7.

The network was accurately modeled 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. 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.

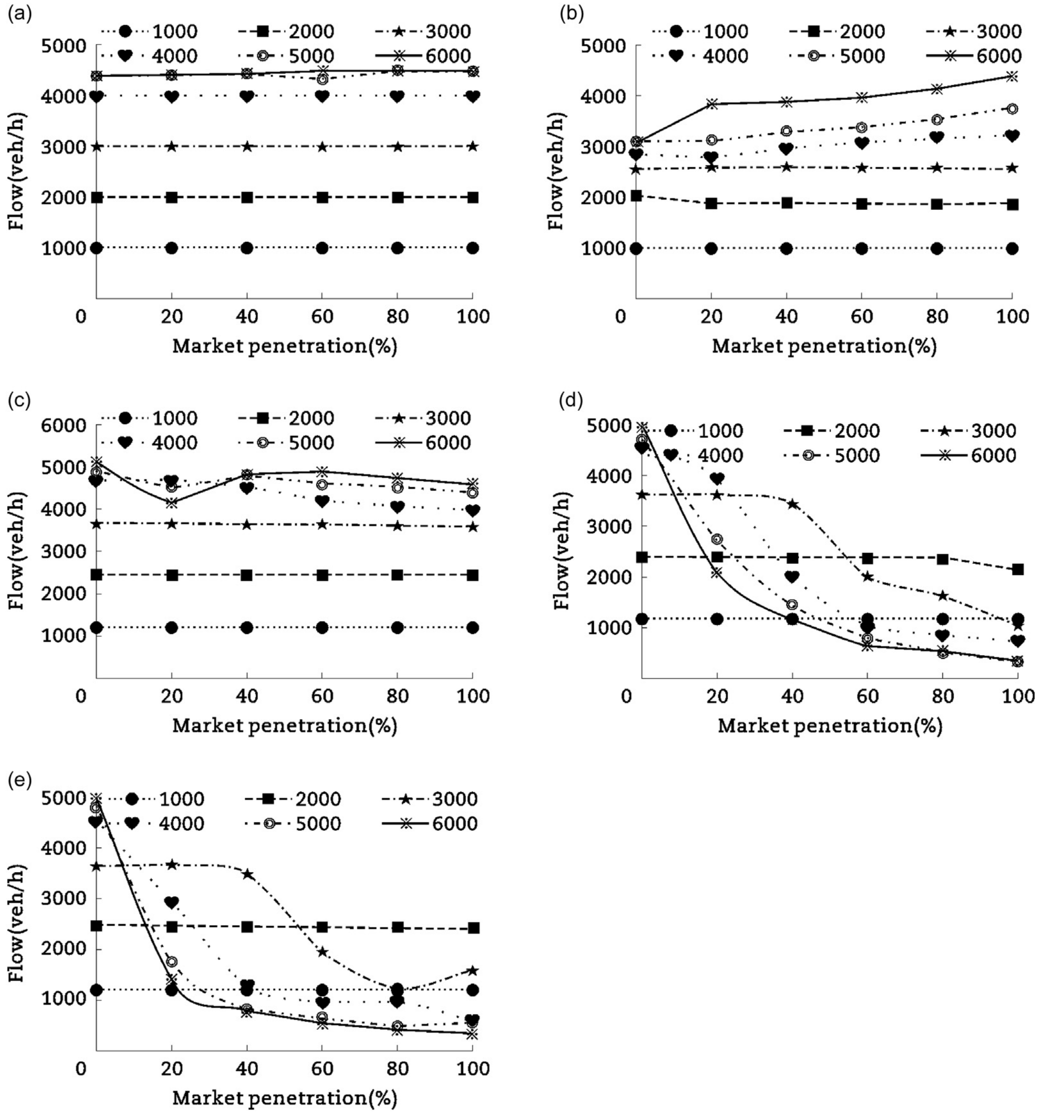

Fig. 5 – Network flow given market penetrations of increasing demand and network complexity. (a) Network 1. (b) Network 2. (c) Network 3. (d) Network 4. (e) Network 5.

The network contains 1825 nodes in total, 227 of which are signalized. Some nodes are with actuated signal plans using loop detectors. There are 4012 links in total, 129 highway links, mainly the Gardiner Expressway, and 3883 urban links. Links were developed using 62 separate link categories.

Demand estimates were created using a 3 step procedure based on the 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, traveler information and place of work. Traveler and trip characteristics can be extrapolated from the 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 containing 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 the 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

Fig. 6 – Study area (Abdulhai et al., 2002).

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 not released under different improved conditions.

7. Mode choice model development

A logit model is used in this study for mode choice as described in Section 3.2. 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 were 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 on the share in non-motorized 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 from taking the average travel time between each internal zone for regular passenger vehicles. Each individual was assigned the average travel time for 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 modeled using information from the Toronto Transit Commission's website to determine stop locations, headways and other necessary information. Transit demands were taken from the TTS and assigned to the model

Fig. 7 – Paramics waterfront microsimulation network (Abdulhai et al., 2002).

Table 1 – Transit assignment parameters (Kucirek, 2012).

Parameter	Value	Meaning
Walk speed	4	Walk speed to or from transit in km/h.
Walk time weight	2	Traveler's value of walk time in comparison to in-vehicle travel time.
Wait time factor	0.5	Distribution of traveler's arrival to transit stops. 0.5 assumes arrival at random.
Wait time weight	2	Traveler's value of wait time in comparison to in-vehicle travel time.
Boarding time weight	1	Traveler'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	

using the origin and destination of each trip as the centre of each TTS zone. Transit assignment parameters are shown in Table 1 along with the definition of each parameter.

The travel time variable was modified for 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, showing the estimate value obtained for the coefficient β in Eq. (1) and the P-value for a t-test to determine the significance of the coefficients. The coefficients show 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. An assumed average speed of 15 km/h was for cycling and 4 km/h was for walk. A similar problem resulted, indicating that it was likely that transit times were causing the discrepancy since transit was 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 had the same overall travel time measure, therefore, a generic variable was used to generate appropriate results. It should be noted that this assumed 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 3. It should be noted that all values are statistically significant.

The McFadden R^2 is used to assess the significance of the model, which takes the form seen in Eq. (3) (Maddala, 1983).

$$R^2 = 1 - \frac{\ln[L(M_{\text{full}})]}{\ln[L(M_{\text{intercept}})]} \tag{3}$$

where $L(x)$ is defined as the likelihood of a model x, and is a measure of how likely the model is to predict the correct result, M_{full} represents the full model developed for this study, $M_{\text{intercept}}$ is an equivalent model just involving the intercept. The two models allow for an exploration of how much predictive capability the chosen variables have. Therefore, the McFadden R^2 is a measure of how much 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 also test the null hypothesis that the two models are statistically the same. In this case, the P-value is less than 2.2×10^{-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 for travel time to gauge the impact on mode share. This was done using an aggregate direct elasticity which indicated 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 Eq. (4) for the individual elasticity and Eq. (5) for aggregate direct elasticities.

$$E_k = (1 - P_{ki}) x_k \beta_i \tag{4}$$

$$E = \frac{\sum_{k=1}^{N} P_{ki} E_k}{\sum_{k=1}^{N} P_{ki}} \tag{5}$$

where E is the elasticity (E_k being the elasticity for individual k), P_{ki} is the probability of individual k using mode i, x_k is the value of the variable for the individual k, β_i is the utility coefficient for mode i.

For use in this study, Eq. (5) indicates the weighted elasticity of auto drivers to change in travel time. Results show the elasticity as −0.5309, indicating that for every

Table 2 – Initial, unused logit model parameters.

Coefficient	Type	Mode	Estimate	P-value
Intercept	Alternative specific	Transit	−1.0150	$<2.2 \times 10^{-16}$
Intercept	Alternative specific	Non-motorized	1.1676	$<2.2 \times 10^{-16}$
In-vehicle time	Generic		0.0023122	$<2.2 \times 10^{-16}$
Wait time	Generic		−0.0019198	1.295×10^{-13}
Walk time	Generic		−0.0006336	4.891×10^{-7}

Table 3 – Logit model parameters.

Coefficient	Type	Mode	Estimate	P-value
Intercept	Alternative specific	Transit	3.22730	$<2.2 \times 10^{-16}$
Intercept	Alternative specific	Cycle	0.22362	0.004644
Intercept	Alternative specific	Walk	4.64050	$<2.2 \times 10^{-16}$
Travel time (s)	Generic		−0.1014446	$<2.2 \times 10^{-16}$
Vehicles in household	Alternative specific	Transit	−2.1405	$<2.2 \times 10^{-16}$
Vehicles in household	Alternative specific	Cycle	−1.7267	$<2.2 \times 10^{-16}$
Vehicles in household	Alternative specific	Walk	−2.3032	$<2.2 \times 10^{-16}$

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 represents 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 separately, the mode choices are calculated separately, and the demands are combined to find the total demand.

8. Results

8.1. *Travel time results and analysis*

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 traveler'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 Fig. 8 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

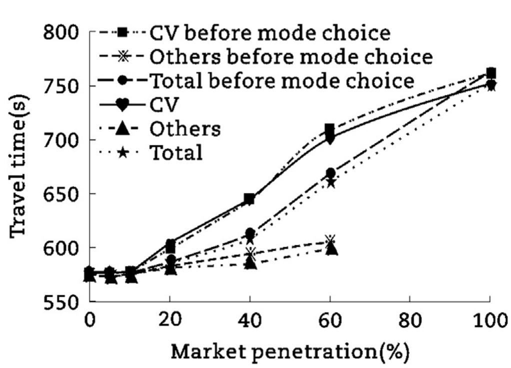

Fig. 8 – Average network travel times before and after the consideration of change in mode choice.

average travel time, in order to determine if it was significantly different from the base case at 0. The results are shown in Table 4.

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 60% 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 (Roughgarden and Tardos, 2000). One possible reason is the suggestion of the same path to too many drivers, with researchers proposing new routing algorithms to overcome this (Adacher et al., 2014). Others have attempted to suggest a more reliable route guidance system (Nie et al., 2012). These results are consistent with the results obtained in the hypothetical test networks presented before.

8.2. *Mode choice results and analysis*

The total mode choice for each market penetration analysis can be seen in Fig. 9.

Mode share does not change for the majority of market penetrations. In these cases, we can conclude that the introduction of connected vehicles does 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 full market penetrations where auto share decreases by 13.3% and is replaced by all the

Table 4 – Analysis results.

Market penetration (%)	P-value	Significant for 95% confidence interval?
5	0.91130	No
10	0.90160	No
20	0.19050	No
40	0.07512	No
60	0.04584	Yes
100	<0.00010	Yes

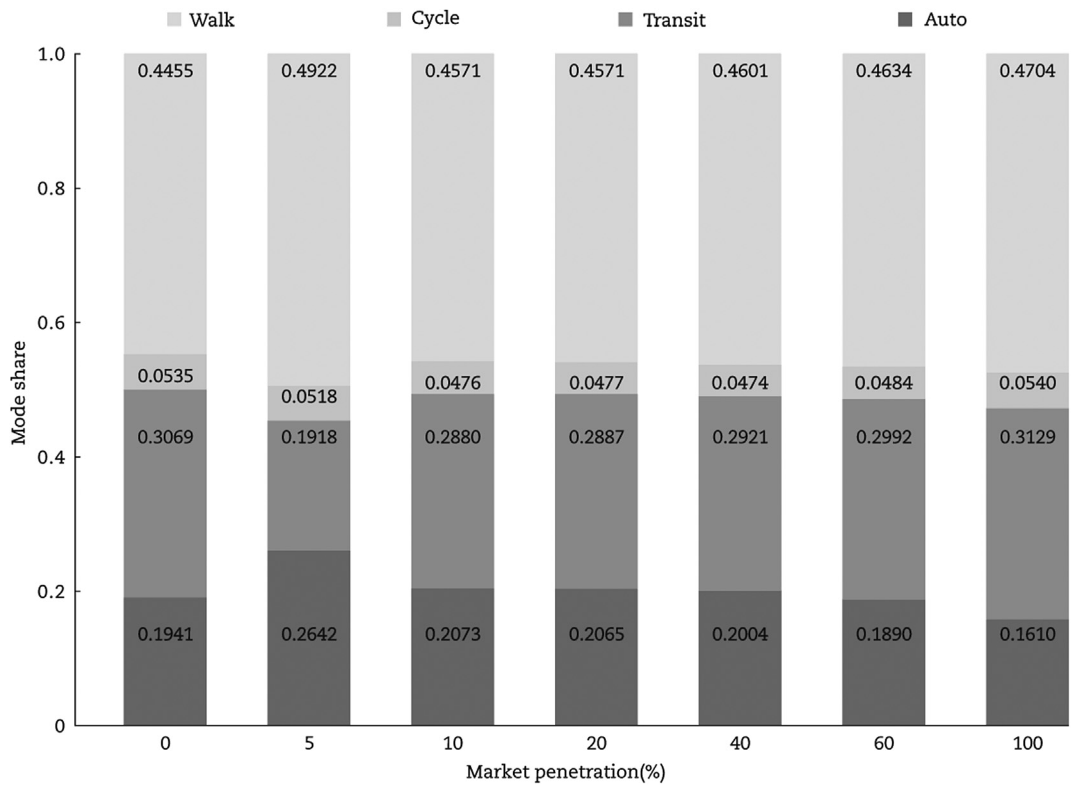

Fig. 9 – Mode shares for various market penetrations of connected vehicles.

other modes. This makes sense that the increase of travel time will push users to other modes.

9. Conclusions

Future research beyond this study could focus on the design of a more complex route guidance system. This could mean developing a system that attempts to improve the limitations of this study or mimics current dynamic route guidance system. In addition, a study could be done with a more complex logit model. A different location could be used that is not as dense as traffic, possibly making it easier to see changes in mode choice.

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.

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