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Integrating Autonomous Vehicle Behavior into Planning Models

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Integrating Autonomous Vehicle Behavior into Planning Models

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Thesis

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Abstract

Integrating Autonomous Vehicle Behavior into Planning Models

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Autonomous vehicles (AVs) may soon be publicly available and are expected to increase both network capacity and travel demand. Reduced safety margins from computer precision may increase network capacity and allow for more efficient intersection controls. AVs also offer the option of repositioning trips to avoid parking fees or share the vehicle between household members, which may increase the total number of vehicle trips and decrease the relative utility of transit. Since AVs may be available within one or two decades, which is within the span of long-term planning models, practitioners may soon wish to predict the effects of AVs on traffic networks. This thesis modifies the four-step planning model commonly used by practitioners to include AV behaviors and capacity improvements. Because dynamic traffic assignment (DTA) offers more realistic flow propagation and intersection control options, the four-step model is modified to incorporate DTA with endogenous departure time choices. To facilitate modeling of AV intersections, the tile-based reservation (TBR) control policy is simplified into a conflict region (CR) model compatible with general simulation-based DTA and with greatly improved computational tractability. Results suggest that although the total number of personal-vehicle trips may almost double (due to repositioning trips to the origin to avoid parking costs), increases in network and intersection capacity can mostly offset or even improve network conditions. Use of dynamic flow propagation instead of static travel time functions in the four-step model results in predictions of increased average travel speed although both static and dynamic planning models predict a high reliance on repositioning trips (i.e., empty-vehicle travel).

To study AV behaviors in DTA, this thesis first integrates DTA into the fourstep model with the addition of departure time choice. This model alone may be useful for practitioners as departure time modeling is a major concern with DTA planning models. Also, the TBR intersection policy has only been studied in microsimulation with heuristic routing strategies. The CR model opens these new techniques to study under UE behavior, which is the first step for the bridge between technology demonstration simulations to models practitioners can use to evaluate implementation. Therefore, the models developed here for the purposes of predicting AV trip and mode choices may themselves become useful tools for other applications.

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1 INTRODUCTION

1.1 Background

Autonomous vehicles (AVs), once only a hallmark of science fiction, have been coming closer to reality in the last two decades. AV prototypes were originally limited to private road competitions such as the DARPA challenge (described in Ozguner et al., 2007), which tested navigation abilities. Developments in image recognition (de la Escalera et al., 2013) and traffic detection and response systems (Li et al., 2004) have led to legal permission for AVs to be test-driven on public roads in several states including California and Nevada under the supervision of a qualified driver (Oakley, 2014). Although AVs are not currently available for purchase, they could be available at car dealerships in a decade or two. Therefore the potential effects on traveler behavior and network congestion are worth consideration.

AVs offer many potential benefits for individual drivers and the traffic network overall which will encourage ownership by drivers and incentives for ownership by governments. First among these is safety; AVs are immune to the effects of distracted and drunk driving, reducing the probability of collisions for both AV owners and other vehicles on the road. Travelers may choose to become AV owners to avoid the temptations of driving while distracted or intoxicated. AVs are likely to reduce other types of incidents as well due to their greater precision and reaction times and the lack of human errors. For example, AVs can better respond to sudden braking by the vehicle in front or hydroplaning events. These safety improvements will be incentives for widespread AV ownership.

In addition to improved safety, travelers may experience reductions in disutility during AV trips which may increase personal vehicle demand. Choice models often distinguish between disutility from to in-vehicle and out-of-vehicle travel time (IVTT and OVTT, respectively), and both are likely to be improved. IVTT may be less onerous for travelers because former distractions such as cell phones and other passengers may become safe ways to pass the time. Travelers could conceivably watch movies or work on laptops as well. Thus the disutility per unit of IVTT may be reduced. The quantity of OVTT may also be reduced through autonomous driving. OVTT for personal vehicles is usually due to distances between destination and parking locations. AVs may negate those by dropping off travelers at the destination then parking autonomously, or vice versa.

The pick-up / drop-off abilities of AVs may be extended to empty repositioning trips. Potential benefits include avoiding parking fees at the destination by parking elsewhere (such as the owners residence) for the alternate cost of additional fuel consumption. This may reduce the monetary advantages that public transit have over personal vehicle travel, leading to a decrease in transit ridership. Another benefit of repositioning trips is the potential for car sharing among household members. A single AV could provide home-to-work transportation for two workers in the same household with sufficiently different work start times.

AVs also offer benefits to transportation network congestion. Lower reaction times may permit reduced following distances and correspondingly higher vehicle density on roads at the same speed. This would result in greater road capacity. Since the cost of increasing road capacity through AVs is paid by AV owners as opposed to government-sponsored road improvement projects, governments might offer incentives for travelers to use AVs.

Dresner and Stone (2004, 2005) developed a tile-based reservation (TBR) control mechanism for AVs to increase intersection utilization. Fajardo et al. (2011) demonstrated that the TBR policy improved over SYNCHRO-optimized traffic signals at a variety of demands. Since arterial signalized intersections and highway merges / diverges are major sources of congestion, TBR could significantly improve network capacity. TBR can be implemented with human drivers on the road (Dresner and Stone, 2007), and the intersection delay benefits would be an additional incentive for AV ownership.

1.2 Motivation

The above potential benefits suggest that, once available for general use, AVs will become preferred over human-driven vehicles. However, the effect of AVs on traffic has received little attention in the literature. Recent workshop presentations at the 2014 meeting of the Transportation Research Board (Pendyala and Bhat, 2014; Polzin et al., 2014) addressed this question from the perspective of activity-based travel behavior, and Fagnant and Kockelman (2013) demonstrated the potential benefits of a shared AV model, but the effects on the traffic network of privately owned AVs have not been studied. Although the timeframe for AV availability is unknown, since they are already being test-driven on public roads, they may be available to the public in one or two decades. That is well within the range of 25 to 30 year planning models used by practitioners to study long term development projects for network improvement. Therefore long-term planning models should consider AV impacts on traveler behavior and vehicle demand.

AVs offer new possibilities for vehicle behavior, but several of those are new options for travelers that may increase demand. Repositioning trips could lead to multiple vehicle trips per traveler trip. Repositioning may also avoid parking fees, reducing the competitiveness of public transit and therefore decreasing transit ridership. The increased utility of AV IVTT due to the possibility to engage in other activities during travel may reduce the disutility of living farther away from the workplace, resulting in longer trips as well. Despite the likelihood of additional demand, network capacity should also increase both on roads due to reduced following distance and at intersections from AV control policies. The increases in capacity may offset the increases in demand. Planning models should include both to capture the impacts on congestion.

The objectives of this thesis are to model the impacts of AV ownership on trip, mode, and route choice. The first question is how AVs affect personal vehicle trips. The possibility of repositioning trips to avoid parking costs or share the vehicle with other household members may result in multiple vehicle trips per traveler trip. Predicting AV owner behavior is an important problem because a complete switch from parking to repositioning could double the number of peak hour trips. The destination and route choices of repositioning trips will determine the impacts on network congestion.

Avoiding parking costs and the lower disutility associated with AV IVTT may encourage travelers to travel in AVs instead of public transit. Transit typically requires higher OVTT in the form of waiting and walking to and from transit stops as well as higher IVTT due to frequent stops and less direct routing. The advantages of transit are lack of parking costs, which can be substantial in downtown regions, and lack of road tolls. AVs may negate both advantages. Repositioning trips could avoid parking costs, and alternate routing could avoid road tolls. Although the latter might increase IVTT, more direct routing, less stops during the travel, and reduced OVTT might offset any increases. As a result, AV availability could result in significant reductions in transit ridership. Transit authorities would benefit from planning model predictions of transit choice to prepare for the impacts of AV availability.

The increases in personal vehicle demand associated with AV repositioning behavior and mode choice preferences contrasts with the increases in supply in the form of greater network capacity. The resulting effects on network congestion could be positive or negative, and will likely vary for specific roads. Overall reductions in congestion, if present, may encourage additional trips as well as reductions in disutility per unit of IVTT in AVs. On the other hand, substantial increases in congestion and travel time could make public transit operating on separate rightof-way more favorable for travelers. The effects are likely to depend on the city network topology and transit options, which is why the model should incorporate traffic network analyses.

AVs may also introduce new routing strategies. Many current traffic assignment models assume that travelers have perfect knowledge of the network as they strive to minimize their travel time. These models predict that travelers may change routes to save a few seconds from a 30 minute trip. Although this may not be fully realistic for human drivers, this behavior is more justifiable for the computerized routing of AVs. In addition, AVs may consider other variables in routing such as fuel consumption. Similar to the cost index used in commercial aviation, travelers may

instruct their AVs to find a path minimizing a generalized cost of fuel and travel time based on value of time. Since congested traffic consumes the most fuel, this strategy may avoid congestion and spread demand over more of the network.

The state of the practice is based on the four-step model described by McNally et al. (2008). Four-step planning separately determines trip distribution, mode choice, and route choice. Although current practice uses static traffic assignment (STA), the more detailed dynamic traffic assignment (DTA) is necessary to include the effects of AV intersection control policy dynamics. This in turn requires that the four-step model be modified to incorporate DTA. The traditional trip distribution and mode choice, as with STA, do not include the time index essential to DTA. Finally, trip distribution and mode choice must be modified to incorporate AV behaviors.

1.3 Problem statements

Because of the numerous new possible behaviors of AVs, thesis develops models to answer the following questions:

- 1. How will the trip, mode, and route choice change as the proportion of AV owners increases? AVs may increase both network efficiency and demand (from repositioning trips as well as less onerous travel). Predicting the combined impact of these opposing effects on the traffic network is an important problem for metropolitan planning organizations studying long-term future design and investment options. Transit authorities are also affected because the avoidance of parking fees through repositioning trips and the potential lower disutility associated with AV travel may greatly decrease transit ridership.
- 2. How does the more accurate flow model of DTA affect trip, mode, and route choice predictions? More realistic flow propagation is an important consideration because AVs may increase link capacity due to reduced headways. The time index in DTA may also improve predictions of the impact of repositioning trips. By definition, repositioning trips depart after the traveler has arrived at the workplace. Although they may greatly increase demand, the

later departure times may reduce their impact on the traffic network for some cities. Because STA cannot capture the effects of later departure times, DTA may yield different predictions of traffic network congestion.

- 3. How can TBR be included in DTA models? TBR can be a significant intersection efficiency improvement (Fajardo et al., 2011). Although previous studies (Vasirani and Ossowski, 2010; Carlino et al., 2012; Carlino et al., 2013) have studied networks of TBR intersections, user equilibrium (UE) routing has yet to be included because of the high computational requirements of TBR. Simulation-based DTA (SBDTA) with discretized vehicles are a prime candidate for including TBR, but require greater computational tractability than a micro-simulation model can provide.
- 4. How can departure time choice be incorporated into DTA planning models? To address the second question, this thesis develops a DTA planning model incorporating AV behaviors. However, integrating DTA into planning is itself an open area of research. Most practitioners (Chiu et al., 2011) would like to incorporate DTA into their planning models. The four-step model is still used by many practitioners, and previous work (Tung et al., 2010; Pool et al., 2012; Duthie et al., 2013) on integrating DTA into the four-step model has used an exogenous departure time profile, which is a major issue with DTA planning models (Peeta and Ziliaskopoulos, 2001).

1.4 Contributions

This thesis develops a four-step model with DTA incorporating AV repositioning trips, road and intersection capacity increases with an endogenous departure time profile. Since the current state of the practice is four-step planning with STA, achieving this goal requires three intermediate steps. First, four-step with STA is modeled to incorporate AV behavior and link capacity improvements. Second, DTA is integrated into the four-step model. Third, the micro-simulation model for the TBR policy is modeled in DTA. These steps are described in more detail below and



Figure 1.1: Contributions of this thesis

illustrated in Figure 1.1.

1.4.1 Static four-step model with autonomous vehicle behavior and capacity

Based on the competing factors of higher vehicle demand and increased capacity, this thesis develops a multi-class STA four-step model using a generalized cost function of travel time, monetary fees, and fuel consumption, to analyze the impact of AV ownership on trip, mode, and route choice. A continuum of AV ownership is considered to analyze not only the impacts of full AV ownership, but also the impact of gradually increasing availability to travelers. A nested logit model predicts the choice between parking, repositioning to the origin to avoid parking fees, and public transit. To model the increases in supply, an increasing capacity function of the proportion of AVs on a link is proposed based on Greenshields' (1935) speed-density relationship.

Demand for the downtown Austin city network (described in Section 3.4.1) is separated into ten VOT classes based on an income distribution, and the impact of gradual AV availability on transit ridership, parking, and congestion is studied during the AM peak with 2 hour trip data. Due to lack of data, all trips are assumed to be home-based work travel. Commercial trips and other types of personal travel may be affected differently. Transit ridership is greatest for low VOT classes (which comprise a significant proportion of the population) because of parking costs. The addition of AVs greatly reduces the monetary cost associated with driving, decreasing transit ridership and greatly increasing the number of vehicle trips. Overall this results in an increase in congestion despite increases in capacity.

1.4.2 Integration of dynamic traffic assignment into four-step planning

The single most challenging obstacle to overcome for DTA planning models is determining the distribution of vehicle departure times (Peeta and Ziliaskopoulos, 2001). Many current models use a common profile across origin-destination (O-D) pairs that does not depend on travel times. For instance, previous work on planning models (Tung et al., 2010; Pool et al., 2012; Duthie et al., 2013) has focused on a minimal modification replacement of STA with DTA by modifying the inputs and outputs of traffic assignment. Vovsha et al. (2012) suggested a time-dependent mode choice, but still assume an exogenous departure time distribution profile of trips that does not vary with O-D travel times. To create an endogenous, origin-destination specific departure time distribution of home-to-work trips for long-term planning, this thesis proposes a trip distribution based on a gravity model based on Vickrey's (1969) arrival time penalty function for departure time choice.

The departure time choice model admits origin-destination (OD) specific preferred arrival times and is analyzed on a city network for two scenarios. First, a universal preferred arrival time is studied to verify that the arrival time penalty performs as expected. Second, a normally distribution arrival time penalty demonstrates the flexibility of the model. The aggregate departure time profile generated by this model is similar to universal bell curve profiles used by previous work. However, it varies by OD; ODs with greater travel times have early departure times, and vice versa.

1.4.3 Autonomous vehicle intersection controls in dynamic traffic assignment

Although the TBR control policy for AVs proposed by Dresner and Stone (2004, 2005) has been implemented in several custom micro-simulators, modeling this control over large city networks has yet to be accomplished due to the computational requirements. This is expected because micro-simulation is less appropriate for modeling city networks. However, this motivates the need for TBR integration into more aggregate models, such as dynamic traffic assignment (DTA). The effects of first-come-first-serve (FCFS) priority TBR on large networks have yet to be studied under user equilibrium.

The computation requirements are of further concern when DTA is solved as a subproblem in four-step planning. Using TBR is computationally infeasible, so this thesis proposes a conflict region (CR) intersection model of TBR compatible with SBDTA models. The CR algorithm reduces the computational complexity of TBR but retains its properties of allowing simultaneous use of the intersection by potentially conflicting vehicles. The proposed model is also compatible with arbitrary vehicle prioritization schemes, including FCFS and auctions. We compare the CR model with results from micro-simulations of the TRB policy and analyze capacity on a single intersection case study. Computation time and convergence results for DTA with CR intersections on a city network are presented to verify the computational feasibility.

1.4.4 Autonomous vehicle behavior in four-step planning with dynamic traffic assignment

The DTA four-step model is combined with repositioning trips and capacity increases to study how AV intersection controls and the more accurate flow propagation of DTA affects mode choice and network congestion. All vehicles are modeled as AVs because the alternative would result in link capacity varying with time as the proportion of AVs on a link changed, and DTA with varying link capacity adds additional complexity. DTA predicts greater average congestion than STA both with and without AVs. However, AVs improve average link speed when the TBR in policy is in use despite the increase in total personal vehicle trips. The decrease in network congestion relies on the intersection capacity improvements though, and AV repositioning trips in a network with traffic signals slightly increase congestion.

1.5 Organization

The remainder of this thesis is organized as follows: Chapter 2 discusses literature relevant to traffic models of AV behavior and integration into planning models. Chapter 3 presents a traditional four-step planning model with STA incorporating repositioning trips and link capacity increases. This model is used to study the effects of gradual ownership of AVs starting from high income travelers and ending with low income travelers on trip, mode, and route choice. However, this model does not include the significant intersection capacity improvements demonstrated by Fajardo et al. (2011). Including these requires the greater detail of DTA.

In preparation for AV behavior analysis in DTA, Chapter 4 presents an integration of DTA into the four-step planning model. The departure time profile is endogenously generated based on the arrival time penalty function of Vickrey (1969). Chapter 5 presents a CR model of the reservation intersection control policy proposed by Dresner and Stone (2004) for use with DTA. The CR model is computationally efficient while preserving the characteristic of simultaneous use of the intersection by conflicting turning movements. The CR model is used to build a four-step planning model with DTA incorporating AV repositioning trips and intersection controls in Chapter 6. Conclusions are discussed in Chapter 7.

2 LITERATURE REVIEW

2.1 Introduction

This chapter discusses literature relevant to developing a DTA planning model including AV behavior. Therefore it is organized into three sections. First, Section 2.2 reviews previous work on traffic models for AVs, including the TBR control policy. Section 2.3 discusses the latest work on DTA in planning models and departure time choice in DTA. Because fuel consumption is considered in the generalized cost function for AV routing, models for energy consumption and eco-routing are discussed in Section 2.4.

2.2 Autonomous vehicles

In the past two decades, autonomous vehicle (AV) research has been quickly maturing. Initially, AVs were limited to private road competitions such as the DARPA challenge (Buehler et al., 2009) to ensure safety. However, developments in image recognition (de la Escalera et al., 2003) and traffic detection and response systems (Li et al., 2004) have led to increased confidence in the ability of AVs to safely navigate the public road network and avoid collisions with other vehicles, bicyclists, and pedestrians. The result is that AVs now have legal permission to be driven on public roads in several states under the supervision of a test driver (Oakley, 2014), and Google has logged over 500,000 miles on public roads (Fisher, 2013).

AVs offer a number of new possibilities for travelers. Several studies (Ford, 2012; Burns et al., 2013; Fagnant and Kockelman, 2014a, 2015a, 2015b) investigated replacing personal vehicle ownership with a large fleet of shared autonomous vehicles (SAVs). Since less than 17% of newer household vehicles are in use at any given time over the course of the day (FHWA, 2009), SAVs could greatly reduce the number of vehicles despite increasing travel (Fagnant and Kockelman, 2013). This could potentially yield significant reductions in energy consumption and greenhouse gas emissions because transportation accounted for 28% of total U.S. emissions in 2011 (EPA, 2013). However, implementing SAVs or taking advantage of other AV technologies such as TBR will likely require considerable initial investments from the government (Fagnant and Kockelman, 2014b). Current AV technology costs may prevent many vehicle owners from purchasing AVs despite the potential savings in operating, parking, and equivalent travel time costs (Fagnant and Kockelman, 2013). Therefore, this thesis first considers a gradual ownership scenario in Chapter 3 based on the assumption that purchasing AVs will slowly become feasible for travelers of different incomes as technology costs are offset by mass manufacturing. Because of the costly investment required to replace personal vehicles with SAVs, this thesis also assumes that AVs are privately owned by travelers.

2.2.1 Traffic models for autonomous vehicles

TBR controls were proposed by Dresner and Stone (2004, 2005) to take advantage of the computer precision and communications abilities of autonomous vehicles. Vehicles request permission from the intersection controller to follow a specific path through the intersection in space-time. The intersection controller divides the intersection into a grid of tiles to check whether vehicles collide, accepting or rejecting requests depending on whether the tiles are occupied at the requested time. This is best illustrated by Fajardo et al. (2011), reproduced in Figure 2.1.

Dresner and Stone (2004, 2005) proposed an FCFS priority based on reservation request time for when the reservations of two vehicles conflict. Fajardo et al. (2011) also demonstrated reductions in delay from TBR with FCFS over SYNCHROoptimized traffic signals for a variety of demands.

Since autonomous vehicle market penetration is likely to occur gradually, Dresner and Stone (2006, 2007) modified TBR to permit use of the intersection by human drivers. This modification consists of a traffic signal for communication with human



Figure 2.1: Reservation conflict check

(a) The two vehicles do not conflict at the specified time. (b) The vehicles conflict in a single tile at the specified time, so the request is rejected (Fajardo et al., 2011).

drivers with timing controlled by the reservation intersection agent. The reservation controller prioritizes AVs reservations, but periodically allows the traffic signal phase to reserve significant portions of the intersection to allow human drivers access.

One challenge in modeling the reservation policy is the computational complexity of simulating vehicles over a grid of tiles over time per intersection. When implemented for real vehicles, each intersection may have a separate computerized controller, but in DTA models all intersections share the same computing power. These requirements are in addition to the computation of vehicle movement or propagation. To reduce computation requirements for city-size networks, Carlino et al. (2012) implemented reservations on the entire intersection as opposed to specific tiles to make single simulations of vehicles on city-size networks tractable. However, this restricts the simultaneous use of the intersection to non-conflicting vehicles. Vehicles can only enter the intersection if the paths of vehicles that already hold or are executing a reservation do not conflict. This differs from the TBR proposed by Dresner and Stone (2004) and may reduce the benefits demonstrated in AIM4 (Fajardo et al., 2011) of TBR over traffic signals. Furthermore, solving SBDTA to account for UE behavior typically requires many simulations. Therefore, implementing TBR directly in DTA is too computationally demanding. At the same time, the DTA model of TBR should preserve its simultaneous use and arbitrary prioritization characteristics to accurately represent the intersection benefits.

2.2.2 Intersection prioritization

Dresner and Stone (2006) proposed giving greater priority to emergency vehicles and vehicles blocking their lane in TBR to allow them access to the intersection as soon as possible. As a corollary, it also motivated the possibility of alternate prioritizations than FCFS. For instance, several studies have considered the use of intersection auctions to give greater priority to high value-of-time (VOT) drivers.

Intersection auctions may be an alternative to the problems of complex or changing tolls and determining toll prices. Due to the communication requirements of implementing auctions, most studies have considered auctions in the context of autonomous vehicles. Schepperle and Böhm (2007, 2008) studied the use of auctions to control vehicle priority in traveling through intersections, and found that average delay weighted by VOT was reduced. Vasirani and Ossowski (2010) similarly found reductions in average travel time from auctions on a network of such intersections. Carlino et al. (2013) added system bids to improve equity and travel time, and found that auctions reduced average travel time for some of the scenarios. However, route choice differences due to UE behavior have yet to be incorporated into network comparisons of intersection auctions.

Although auctions have greater communication requirements, existing technologies come close to meeting them. de Palma and Lindsey (2011) noted that most tolling facilities in the United States use dedicated short range communications technology to identify vehicles. In addition to transmitting vehicle identification, these technologies could be modified to transmit an auction bid as well. Of greater difficulty is communicating to drivers whether they have won the auction and are permitted to use the facility. Since no such system yet exists, Schepperle and Böhm (2007, 2008), Vasirani and Ossowski (2010), and Carlino et al. (2013) studied auctions in the context of autonomous vehicle intersection controls. Auctions at intersections may offer further advantages in terms of congestion reduction. First, they are integrated with autonomous vehicle intersection controllers, obviating the need for investment in separate facilities. Second, intersections (both arterial and highway merge/diverge) are often major sources of congestion. Although tolling links will reduce the backwards propagation of congestion, pricing the source of the congestion could be more effective.

2.2.3 Link efficiency from autonomous vehicles

Link capacity improvements have primarily been studied from the perspective of connected vehicles (CVs) through adaptive cruise control (ACC) (Marsden et al., 2001) that may be connected with other equipped vehicles through wireless communications. ACC is inherently compatible with AVs, although cooperative ACC (CACC) may require additional onboard technology. Models of CACC have also made extensive use of micro-simulation to study the impact of reduced headways. Van Arem et al. (2006) showed that CACC improves capacity through micro-simulation. Kesting et al. (2010) used an acceleration behavior model to predict the theoretical capacity, using a linear regression to extrapolate between different proportions of CVs and non-CVs. ACC also increases stability and shockwave speed (Schakel et al., 2010), although predicting these in DTA requires further study. However, without a study on how AV capacity may be modeled in STA and DTA, this thesis proposes a heuristic based on Greenshields' (1935) model to scale capacity with the proportion of AVs.

2.3 Integration of dynamic traffic assignment into planning

The problem of integrating departure time choice into DTA, which the proposed model attempts to address, has received some attention in the literature although not in combination with the broader four-step planning model. Previous work also highlighted the particular theoretical concerns presented in an integration of DTA with the four-step model, some of which are addressed by the departure time choice model in this paper. There is a considerable body of literature on the traditional four-step model as well as DTA, which are relevant to the contributions made in this thesis.

2.3.1 Dynamic traffic assignment

There has been substantial research conducted in the area of traffic assignment, including many model formulations and extensions for both static and dynamic flow models. DTA improves on steady-state models for city network analyses, and can be calibrated to replicate observed traffic patterns (Lin et al., 2011). For a review of the development and utility of DTA, see Chiu et al. (2011). Improvements of DTA over STA include queue propagation to more accurately model congestion and time-varying traffic conditions.

DTA can be computationally challenging, and using it as a subproblem for planning processes can result in discouraging computational requirements. However, similarities between DTA runs, such as the identical network and possibly similar trip tables, can be used to reduce the total time spent on DTA. For instance, Bar-Gera and Boyce (2003) proved convergence of a planning algorithm with embedded traffic assignment based on an origin-based algorithm. Another option is warm-starting, or providing an initial assignment to expedite convergence. Dial (2006) found that, for Algorithm B, static model computation time to reach a specified cost gap could be reduced by starting with an existing solution for the same network with marginally different trips. Levin et al. (2014a) studied heuristics for warm-starting DTA based on the output of STA. Similar techniques are used in this paper for warm-starting DTA on a modified trip table with a previous DTA solution.

2.3.2 Departure time choice

Peeta and Ziliaskopoulos (2001) noted the importance of departure time choice for DTA planning models, which can have a substantial impact on peak hour demand patterns and therefore congestion predictions. These congestion differences could impact policy decisions regarding level of service (TRB, 1965) and environmental objectives since congestion greatly increases energy consumption and greenhouse gas emissions. López and Monzón (2010) presented a framework for assessment of multiple criteria, one of which might be a comparison of environmental impact against the system optimum (Aziz and Ukkusuri, 2012). Concentration of demand into small periods during peak hours due to similar departure and arrival time preferences, as observed in the experimental results, could affect predictions of greenhouse gas emissions when compared with a more distributed departure time profile.

The problem of determining departure times from observed data has been studied (summarized in Bera and Rao, 2011), but reliance on field observations can be difficult for planners. Identifying demand matrices from observed counts is an underdetermined problem, resolved by the use of prior information, and the addition of a departure time index compounds the difficulty (Dixon and Rilett, 2002). Most of the time profile studies in the literature have focused on simultaneous route and departure time choice (SRDTC) (Li et al., 1999; Ziliaskopoulos and Rao, 1999; Friesz et al., 2001). Studies include both analytical and simulation-based models. Most SRDTC models are more focused on short-term, day-to-day travel behaviors, and do not account for trip distribution choices (such as residence and job location) that are possible in longer-term planning. Szeto and Lo (2004) and Han et al. (2011) extended the simultaneous choice to a cell-based DTA with elastic demand, in which travelers have a choice whether to travel. However, using trip distribution and mode choice provide information about transit travel, and their departure and arrival times, that elastic demand models lack. Such information about transit is often of interest to metropolitan planning organizations.

One important question is the objective travelers seek to achieve through their departure time choice. During the morning peak, trips are typically constrained by workplace required arrival times as well as other trip costs. Because travel times are typically less during non-peak hours, a reliance on travel time alone to predict departure time choice can result in an unrealistic number of trips departing at nonpeak hours. Arrival time has previously been modeled through an asymmetric arrival time penalty function, introduced in the context of a route and departure time choice model specific to the morning commute by Vickrey (1969). Travelers place penalties on arriving early or late, with the penalty for arriving late weighted more heavily. These penalties are incorporated into a generalized travel cost function.

The arrival time penalty function has been used frequently in bottleneck models. For instance, Liu and Nie (2011) used this arrival time penalty in a two-route bottleneck model with tolls and departure time choice, comparing two different value of time classes of weights for their generalized cost function. Gonzales and Daganzo (2012) also analyzed the bottleneck problem for the morning commute, developing pricing strategies and proving the existence of user equilibrium under the assumption of a wish curve for departure time choice.

Arrival time penalty has also been considered in several larger-scale models. Bliemer et al. (2010) proposed an elastic demand, route, and departure time choice model to analyze the effect of rewards on departure time choice. However, their model was designed for short-term choices rather than long-term planning, and focuses on the impact of rewards. Bellei et al. (2006) proposed a nested logit model incorporating trip distribution and mode choice, and use a departure time penalty function for departure time choice. Their model is well suited to analyzing home-based other trips, as morning peak home-based work travelers are often more constrained by arrival time at work. This paper extends the arrival time penalty influence on departure time choice, to long-term planning models for the morning peak on a city network scale.

Although departure time choice has been combined with short-term decisions, such as route choice, in previous work, Travel time is one factor for trip or destination choices in terms of residence location and work or school, and travel time varies with departure time. Since departure time is also constrained by preferred arrival times, departure time choice is reasonable to include in the long-term context we think it quite plausible that households (when making choices about employment and housing location) consider the implications on morning departure time choice along with the commute time itself.

2.3.3 Integration with travel demand

While the previous sections describe some of the research pertaining to departure time choice and planning models, there currently are very few studies that have approached the problem of integrating these ideas within a common framework. Tung et al. (2010) describe one possible approach for integrating DTA with the four-step model by a simple replacement of STA with DTA within the final model step without modifying any other steps. However, the study uses a time-of-day model to spread trips among five periods throughout the day. Duthie et al. (2013) identified the lack of time-varying trip distribution and mode choice in the literature despite examples of high variance for specific origin-destination pairs and suggested mode choice applied at time intervals, using time-varying travel times. Finally, the work included a study of fundamental differences between static and DTA which are relevant to integrated planning models.

Vovsha et al. (2012) also used a time-dependent nested logit model mode choice using time-varying costs as input. However, their trip distribution is based on averages from data taken over a significant survey period. They also identified the need for more robust DTA models, particularly to address the fixed distribution profile. They suggested activity-based modeling (Bhat and Koppelman, 1999), which determines trips from specific activities rather than a gravity model of travel costs. The activity-based approach can yield more realistic results through the use of more extensive time-use data. The specific detail in the activities is well-suited to DTA, and Lin et al. (2008) described the problem of integrating DTA with an activity-based planning model. Ramadurai and Ukkusuri (2011) improved the activity choice and DTA integration with a bush-based method that obviates path enumeration. However, the four-step model still has widespread use among practitioners, and moving to an activity-based model would require significant changes both in input data and software which may not be feasible in the immediate future.

2.4 Energy consumption and eco-routing

Eco-routing, or choosing routes to minimize fuel consumption or emissions, has received increasing attention in the literature in the past decade as global warming awareness increases. The models presented in this thesis for AV routing behavior assume that AVs seek to minimize a generalized cost function of travel time, fuel consumption, and road tolls based on a value of time (VOT). Although such routing may be too complex for human drivers, it is well within the capabilities of computers. Flight management systems used in commercial aviation already adjust speed to minimize a generalized cost function of fuel consumption and operating costs, weighted by the cost index. Therefore it is feasible that similar routing functions may be incorporated into AVs. This section discusses previous work on integrating energy consumption and emissions into traffic models. It concludes by reviewing studies on eco-routing.

Environmental cost functions have been incorporated into traffic assignment components in past studies. Following the initial work of Merchant and Nemhauser (1978) with regards to the DTA modeling approach, classical path-based system optimal DTA models (Peeta and Mahmassani, 1995; Ghali and Smith, 1995) assigned trips to minimize the objective function. Readers are directed to more detailed research by Ran et al. (1994), Bernstein et al. (1993), Friesz et al. (1993), and Wie et al. (1995), which conducted some of the pioneering work in terms of new formulations and novel solution approaches.

One of the earliest studies to explicitly include environmental objectives in the form of emission factors in standard assignment practices was by Tzeng and Chen (1993), who developed a multi-objective traffic assignment method using nonlinear programming techniques and produce various solutions that minimize carbon monoxide (CO) emissions, assuming fixed link-specific emissions. Rilett and Benedek (1994) proposed an equitable traffic assignment with environmental cost functions and consider UE and system optimal traffic assignments. The same study was extended by Benedek and Rilett (1998) with an equitable strategy trying to minimize both CO emissions and travel time. Yin and Lawphongpanich (2006) used a bi-objective function where objectives are reducing congestion and emissions through toll pric-Sugawara and Niemeier (2002) developed an emission-optimized assignment ing. model and conclude that the emission-optimized assignment is most effective under low to moderately congested conditions, saving 30% of CO emissions. Nagurney et al. (1998) developed a multi-criteria network equilibrium model with environmental criteria and used a fixed amount of CO emission rate per traveler per link. In a separate study, Nagurney (2000) examined distinct paradoxical phenomena occurring in congested urban networks regarding total emissions and demonstrated that so-called network 'improvements' may actually result in higher emissions. More recently, Ahn and Rakha (2008) investigated the impacts of route choice decisions on vehicle energy consumption and emission rates for different vehicle types using microscopic and macroscopic emission estimation tools and report that the faster highway route is not always the best from an environmental perspective. Rakha et al. (2012) presented the INTEGRATION microscopic framework and develops eco-routing algorithms based on vehicle sub-populations and individual agents, and observed a 15% savings in fuelconsumption levels. Kolak et al. (2013) introduced sustainability measures based on emission amounts and concluded that simultaneously applying the toll pricing and capacity enhancement policies is in general more effective in serving demand and reducing the emission compared to implementing them individually.

Some studies explicitly model new strategies for finding eco-routes. Ericsson et al. (2006) studied the tradeoff between a navigation system based on carbon dioxide emissions rather than shortest distance or time. Their results indicated that these are not necessarily served by the same route and reductions of the order of 8% can be achieved when optimizing for fuel savings. Barth et al. (2007) and Minett et al. (2011) elaborated on energy and fuel efficiency by investigating the performance of energy optimized routes. Further studies have conducted pollutant-specific ecorouting analysis such as Frey et al. (2008) who showed the effect of road grade on emissions and noted that best total fuel use and mono-nitrogen oxide emissions can dictate different eco-routes. Ahn and Rakha (2008) and Bandeira et al. (2006) in separate studies showed that minimizing different pollutants can result in different optimal routes.

3 STATIC FOUR-STEP PLANNING FOR AUTONOMOUS VEHICLES

3.1 Introduction

Much of the literature on AVs has addressed the technological hurdles in putting AVs safely on the road. Literature on transportation models for AVs include the proposal of a reservation-based intersection control policy by Dresner and Stone (2004) that could increase road network capacity when AVs are a significant share of the traffic. A more aggregate question is how AV ownership will affect trip and mode choice. Recent workshop presentations at the 2014 meeting of the Transportation Research Board (Pendyala and Bhat, 2014; Polzin et al., 2014) addressed this question from the perspective of activity-based travel behavior. However, there is yet to be any literature published on travel demand models to account for AV benefits. Therefore, the purpose of this chapter is to modify the four-step planning model to address the question of how AV ownership will affect transit demand during the highly congested peak hours. Trip and mode choice is analyzed through generalized costs of travel time, monetary fees, and fuel consumption. AVs are expected to increase trips because of the possibility of empty repositioning trips to avoid parking costs and allow other household members to share the vehicle. On the other hand, AVs also have the potential to increase road capacity. An increasing capacity function is proposed in Section 3.2 based on Greenshields' (1935) speed-density relationship as the proportion of AVs increases.

The contributions of this chapter are developing a multi-class four-step model using a generalized cost function of travel time, monetary fees, and fuel consumption to analyze the impact of AV ownership on trip, mode, and route choice. Three mode options of parking, repositioning, and transit are considered using a nested logit model. A continuum of AV ownership is considered to analyze not only the impacts of full AV ownership, but also the impact of gradually increasing availability to travelers. The model is analyzed on a city network to demonstrate the potential effects on actual planning predictions.

The remainder of this chapter is organized as follows. Section 3.2 describes the generalized cost function and the Section 3.3 describes the modifications made to the four-step model to include the AV round-trip choice. Section 3.4 presents experimental results from the Austin downtown network, and conclusions are discussed in Section 3.5.

3.2 Methodology

The fact that travel cost may impact trip, mode, and route choice is well-known and fundamental in most combined demand and assignment models. Autonomous vehicles (AVs) could conceivably affect all three aforementioned traveler choices by changing the utility of personal vehicle travel. AVs can avoid parking costs by dropping off travelers, then returning to the owner's residence for free parking, thereby reducing the cost of driving relative to transit. These reduced costs may affect trip choice, not only because of a reduced desire for some travelers to choose origins and destinations near transit to avoid parking costs, but also because travelers may partake in activities besides driving while traveling by AV. Finally, the change in demand on the road network due to changes in trip distribution and mode choice will affect travel times and equilibrium flow.

To model the effect of AVs on demand and route choice, this chapter presents a modified four-step planning model with the addition of an AV round trip instead of a one-way trip with parking. Road capacity is formulated as a function of proportion of AVs on the road, based on Greenshields' (1935) speed-density relationship. To more accurately model the costs incurred by the additional driving, a fuel consumption model is incorporated into the generalized cost function.
3.2.1 Assumptions

Because AVs are still in the early stages of testing, experimental data on AV owner behavior and AV improvements in traffic network capacity is not available. Theoretical studies such as Dresner and Stone (2006) have predicted significant improvements in intersection flow, but link capacity changes, if any, have not been studied. Therefore we make the following assumptions about traveler behavior and capacity:

- 1. AV market penetration will occur over a number of years as the purchase price gradually becomes viable for travelers of all incomes. Therefore our model is built on the four-step planning model, which is often used for long-term predictions. A long-term model may be useful to practitioners including the impact of AVs in 20 or 30 year planning models.
- 2. AV drivers have the option of parking (with a possible parking fee) or sending their AV back to the origin and incurring fuel costs. Although activity-based models (Bhat and Koppelman, 1999) may predict additional utility benefits by making the AV available to other travelers in the household, techniques to model such benefits in the four-step planning model are less clear. Repositioning to alternate parking locations other than the origin for a reduced parking cost is also a realistic option. However, without parking cost data, modeling the utility resulting from parking at different locations is difficult. This results in three mode options: parking, repositioning, and transit. A nested logit model is used to decide between driving and transit, and parking and repositioning.
- 3. Travelers seek to minimize a generalized cost of time, fuel, and tolls/parking fees. AVs are assumed to choose a route that minimizes this combined cost function, including fuel consumption. Travelers are divided into value-of-time (VOT) classes, and VOT is used to convert travel time to units of money. Incorporating fuel consumption into route choice, or eco-routing has been previously studied by Rakha et al. (2012) and Yao and Song (2013), as well as others, and AV routing algorithms could incorporate eco-routing technology. Although

requiring travelers to choose a VOT for their trip routing may seem restrictive, airlines already do this through their cost index.

- 4. A static traffic assignment (STA) model is used with four-step planning. Although Tung et al. (2010) and Duthie et al. (2013) have incorporated DTA into the four-step model, without literature on modifying the greater detail in DTA (such as intersection dynamics) for AVs, DTA could easily be less accurate. Additionally, trip distribution and mode choice have potential errors due to the possible behaviors of AV drivers. DTA is more sensitive to demand and departure time variability, and may exacerbate any errors in demand predictions. DTA also has the downside of requiring more computational resources. Therefore a STA model, which is commonly used with the four-step model, was chosen for this study.
- 5. Lower reaction times and greater precision of AVs are assumed to reduce the necessary following distance and correspondingly increase the jam density. Link jam density is then a function of the proportion of AVs on the link. Capacity is assumed to be a linearly related to jam density, as with Greenshields' (1935) model, to predict the increase in capacity as a function of AVs. This relationship was chosen because although AVs may have the reaction time to support minimal headways at any speed, the vehicle may not have the braking authority to match maximum braking behavior of the vehicle ahead. Therefore, as speed increases, headways must increase as well, even for AVs. Although Greenshields' relationship is designed for use with hard capacities in DTA as opposed to the capacity of the BPR function, it is used here only to scale the original capacities in the static network. In the absence of studies estimating roadway capacity improvement as a function of AV proportion, we believe this assumption is reasonable. Greenshields's model also results in the favorable property of the travel time function being monotone increasing with respect to increases in AV flow (despite increases in capacity).

These assumptions are made for the purposes of a long-term planning model because the impact of AVs has not been well studied. However, with AVs in testing on public roads, 20 or 30 year predictions by metropolitan planning organizations may soon wish to include the effects of AV ownership in their analyses of travel demand.

3.2.2 Impedance function

The computer precision and reaction times of AVs allows reduction of headways while maintaining safety in the event of sudden deceleration of the vehicle ahead. These reduced headways increase density, permitting greater roadway capacity. To model this, the travel time model was based on the well-known Bureau of Public Records (BPR) travel time function with capacity as a function of the proportion of AVs on the road:

$$t_{ij}(\boldsymbol{x}_{ij}) = \hat{t}_{ij} \left(1 + \aleph_{ij} \left(\frac{\sum\limits_{y \in Y} x_{ij}^y}{Q_{ij}(\boldsymbol{x}_{ij})} \right)^{-i_{ij}} \right)$$
(3.1)

where $t_{ij}(\boldsymbol{x}_{ij})$ is travel time when the flow is \boldsymbol{x}_{ij} , flow specific to class y is x_{ij}^y , \hat{t}_{ij} is the free flow travel time, Q_{ij} is the capacity, and \aleph_{ij} and \beth_{ij} are calibration constants for link [i, j].

Since the VOT varies across the population, the population of travelers is instead divided among a set of discrete classes Y, with each $y \in Y$ having a VOT of ν_y . Each class uses AVs entirely or not at all, denoted by the boolean variable ξ_{AV}^y . ξ_{AV}^y is exogenous in this model because ownership decisions depend also on AV pricing relative to individual household income and utilities. This is not restrictive because any traveler class with owners of both AVs and non-AVs can be separated into two classes with the same VOT. (If a VOT class includes owners of both AVs and non-AVs, we assume that the market penetration is known).

We derive below conditions under which $t_{ij}(\mathbf{x}_{ij})$ is monotone increasing with respect to any x_{ij}^y . This is necessary but not sufficient for formulating the multiclass traffic assignment problem as a convex program (Marcotte and Wynter, 2004). Indeed, we have

$$\frac{\partial t_{ij}}{\partial x_{ij}^y} = \hat{t}_{ij} \aleph_{ij} \beth_{ij} \left(\begin{pmatrix} \left(\sum_{y' \in Y} x_{ij}^{y'} \right)^{\beth_{ij-1}} \left(\frac{1}{Q_{ij}(\mathbf{x}_{ij})} \right)^{\beth_{ij}} - \\ \left(\left(\sum_{y' \in Y} x_{ij}^{y'} \right)^{\beth_{ij}} \left(\frac{1}{Q_{ij}(\mathbf{x}_{ij})} \right)^{\beth_{ij+1}} \frac{\partial Q_{ij}(\mathbf{x}_{ij})}{\partial x_{ij}^y} \end{pmatrix}$$
(3.2)

Then $\frac{\partial t_{ij}(\boldsymbol{x}_{ij})}{\partial x_{ij}^y} > 0$ if

$$Q_{ij}\left(\boldsymbol{x}_{ij}\right) > \left(\sum_{\boldsymbol{y}' \in Y} x_{ij}^{\boldsymbol{y}'}\right) \frac{\partial Q_{ij}\left(\boldsymbol{x}_{ij}\right)}{\partial x_{ij}^{\boldsymbol{y}}}$$
(3.3)

Equation (3.3) implies that capacity must exceed the change in capacity due to additional x_{ij}^y flow; otherwise $\frac{\sum\limits_{y'\in Y} x_{ij}^{y'}}{Q_{ij}(\boldsymbol{x}_{ij})}$ may decrease resulting in a decrease in $t_{ij}(\boldsymbol{x}_{ij})$.

A capacity function based on the well-known Greenshields' (1935) speeddensity relationship and an increasing jam density function of the proportion of autonomous vehicles is shown to satisfy equation (3.3) under reasonable assumptions. Greenshields' relationship predicts

$$\boldsymbol{v}_{ij} = \hat{\boldsymbol{v}}_{ij} \left(1 - \frac{k_{ij}}{K_{ij}} \right) \tag{3.4}$$

where v_{ij} is vehicle speed, \hat{v}_{ij} is free flow speed, k_{ij} is density, and K_{ij} is jam density on link [i, j]. Based on equation (3.4), capacity is $Q_{ij} = \frac{K_{ij}\hat{v}_{ij}}{4}$, a linear function of jam density. Therefore $Q_{ij}(\boldsymbol{x}_{ij})$ is also assumed to be a linear function of jam density:

$$Q_{ij}\left(\boldsymbol{x}_{ij}\right) = \rho K_{ij}\left(\boldsymbol{x}_{ij}\right) \tag{3.5}$$

Jam density is assumed to be a function of the proportion of AVs on the road. Human drivers are on average expected to require some headway \exists_{HV} including the length of the vehicle ahead, with AVs requiring a distance $\exists_{AV} < \exists_{HV}$. Jam density is then

$$K_{ij}(\boldsymbol{x})ij) = \frac{1}{\neg_{\rm HV}} \left(\frac{\sum\limits_{y \in Y} \left(x_{ij}^y \left(1 - \xi_{\rm AV}^y \right) \right)}{\sum\limits_{y \in Y} \left(x_{ij}^y \right)} \right) + \frac{1}{\neg_{\rm AV}} \left(\frac{\sum\limits_{y \in Y} \left(x_{ij}^y \left(\xi_{\rm AV}^y \right) \right)}{\sum\limits_{y \in Y} \left(x_{ij}^y \right)} \right)$$
(3.6)

The capacity function defined by equations (3.5) and (3.6) is shown to be monotone increasing with respect to any x_{ij}^y under the assumption that $2 \mathbb{1}_{AV} > \mathbb{1}_{HV}$. This assumption is reasonable considering highway vehicle spacing at jam density was estimated at $\mathbb{1}_{HV} = 27.3$ feet for one city by Van Aerde and Rakha (1995), and Elefteriadou et al. (1997) suggested $\mathbb{1}_{AV} > 17$ feet length for a passenger car equivalent, which is a lower bound on spacing.

Proposition 1. If
$$2 \mathbb{I}_{AV} > \mathbb{I}_{HV}$$
 then $Q_{ij}(\boldsymbol{x}_{ij}) > \left(\sum_{y' \in Y} x_{ij}^{y'}\right) \frac{\partial Q_{ij}(\boldsymbol{x}_{ij})}{\partial x_{ij}^{y}} \ \forall_{x_{ij}^{y}}$.
Proof. Since $2\mathbb{I}_{AV} > \mathbb{I}_{HV}, \ \mathbb{I}_{AV} > \mathbb{I}_{HV} - \mathbb{I}_{AV}$ and $\mathbb{I}_{AV} \sum_{y \in Y} x_{ij}^{y} > (\mathbb{I}_{HV} - \mathbb{I}_{AV}) \sum_{y \in Y} x_{ij}^{y}$.
Since $\mathbb{I}_{HV} \geq \mathbb{I}_{AV}$,

$$\sum_{y \in Y} \left(\exists_{AV} x_{ij}^y \xi_{AV}^y \right) + \sum_{y \in Y} \left(\exists_{HV} x_{ij}^y \left(1 - \xi_{AV}^y \right) \right) > \left(\exists_{HV} - \exists_{AV} \right) \sum_{y \in Y} x_{ij}^y$$
(3.7)

Since capacity can be rewritten as

$$Q_{ij}\left(\boldsymbol{x}_{ij}\right) = \rho \frac{1}{\exists_{\mathrm{HV}}} \frac{1}{\sum_{y \in Y} x_{ij}^{y}} \left(\sum_{y \in Y} \left(\exists_{\mathrm{AV}} x_{ij}^{y} \left(1 - \xi_{\mathrm{AV}}^{y} \right) \right) + \sum_{y \in Y} \left(\exists_{\mathrm{HV}} x_{ij}^{y} \xi_{\mathrm{AV}}^{y} \right) \right)$$
(3.8)

then

$$\frac{\partial Q_{ij}\left(\boldsymbol{x}_{ij}\right)}{\partial x_{ij}^{y}} = \rho \frac{1}{\exists_{\mathrm{HV}} \exists_{\mathrm{AV}}} \left(\frac{\frac{1}{\sum\limits_{y' \in Y} x_{ij}^{y'}} \left(\left(1 - \xi_{\mathrm{AV}}^{y}\right) \exists_{\mathrm{AV}} + \xi_{\mathrm{AV}}^{y} \exists_{\mathrm{HV}} \right) - \frac{1}{\left(\sum\limits_{y' \in Y} x_{ij}^{y'} \right)^{2}} \left(\sum\limits_{y' \in Y} \left(\exists_{\mathrm{AV}} x_{ij}^{y'} \left(1 - \xi_{\mathrm{AV}}^{y}\right) \right) + \sum\limits_{y' \in Y} \left(\exists_{\mathrm{HV}} x_{ij}^{y'} \xi_{\mathrm{AV}}^{y} \right) \right) \right)$$
(3.9)

$$Q_{ij}\left(\boldsymbol{x}_{ij}\right) > \left(\sum_{y'\in Y} x_{ij}^{y'}\right) \frac{\partial Q_{ij}(\boldsymbol{x}_{ij})}{\partial x_{ij}^{y}} \text{ simplifies to}$$
$$\sum_{y'\in Y} \left(\exists_{AV} x_{ij}^{y'} \xi_{ij}^{y'} + \sum_{y'\in Y} \left(\exists_{HV} x_{ij}^{y'} \left(1 - \xi_{AV}^{y'}\right) \right) \right) > \sum_{y'\in Y} x_{ij}^{y'} \left(\exists_{HV} - \exists_{AV} \right)$$
(3.10)

which is satisfied because equation (3.7) is true.

3.2.3 Fuel consumption

To incorporate the multiple types of costs incurred by different modes, such as transit fees and travel time, a generalized cost function is required. Monetary fees and travel time do not fully encompass the cost of an AV making a round trip instead of a one-way trip with parking. The associated cost to the traveler of the AV's return leg is not travel time (for the traveler is not in the vehicle), and road tolls can be avoided by route choice. However, regardless of the route, the return trip incurs additional fuel consumption. Therefore, the fuel consumption function found by Gardner et al. (2012), based on a regression equation from MOVES (US EPA, 2009) data, was used:

$$\tilde{F}_{ij}(\boldsymbol{v}_{ij}) = 14.58 \left(\boldsymbol{v}_{ij}\right)^{-0.6253} \tag{3.11}$$

where v_{ij} is vehicle speed in miles per hour and $\tilde{F}_{ij}(\cdot)$ is energy consumption in kilo-Watt hours per mile on link [i, j]. This function is monotone decreasing with speed, therefore monotone increasing with travel time, allowing its use as part of a generalized cost function for the standard user equilibrium assignment. Fuel consumption was included for all personal vehicle trips one-way with parking and AV round-trip, and converted into money through the price of gasoline, \exists , which was assumed to be constant and the same for all vehicles on the network. For a link $[i, j] \in E$ (where E is the set of links) with length L_{ij} in miles, the fuel consumed over the link for a travel time of t_{ij} in hours, $F_{ij}(t_{ij})$, is then

$$F_{ij}(t_{ij}) = \frac{L_{ij}}{36.44 \text{ kW/gal}} \left(14.58 \left(\frac{L_{ij}}{t_{ij}} \right)^{-0.6253} \right)$$
(3.12)

where 36.44 kW/gal is the energy content of gasoline (Fuel Properties Comparison).

3.2.4 Generalized cost

When creating generalized costs based on travel time and money, an important variable is the VOT for conversion to a single unit. Travelers with a high VOT may burn more fuel and use tolled roads to reduce travel time, whereas travelers with a low VOT may be more reluctant to incur monetary costs. The generalized cost function for driving on link [i, j], $c_{ij}^{y,\text{DR}}(\boldsymbol{x}_{ij})$ is a combination of travel time, fuel consumption, and road toll τ_{ij} :

$$c_{ij}^{y,\text{DR}} = \nu_y t_{ij} \left(\boldsymbol{x}_{ij} \right) + \Im F_{ij} \left(t_{ij} \left(\boldsymbol{x}_{ij} \right) \right) + \tau_{ij}$$
(3.13)

For a parking fee of ς_s^{PK} , the cost of a one-way driving trip from r to s followed by parking is

$$C_{rs}^{y,\text{PK}}(\pi) = \varsigma_s^{\text{PK}} + \sum_{(i,j)\in\pi} c_{ij}^{y,\text{DR}}(\boldsymbol{x}_{ij})$$
(3.14)

where π is the route.

For the return leg of AV round-trips, with no passenger, travel time is not a factor, so the notation $c_{ij}^{0,\text{DR}}$ with $\nu_0 = 0$ is used to denote the cost of driving with 0 VOT. Cost of an AV round-trip, using path π_1 for travel from r to s and path π_2 for travel from s to r, is

$$C_{rs}^{y,\text{AV}}(\pi_1,\pi_2) = \sum_{(i,j)\in\pi_1} c_{ij}^{y,\text{DR}}(\boldsymbol{x}_{ij}) + \sum_{(i,j)\in\pi_2} c_{ij}^{0,\text{DR}}(\boldsymbol{x}_{ij})$$
(3.15)

The cost of traveling on link [i, j] using transit is similarly

$$c_{ij}^{y,\mathrm{TR}}\left(\boldsymbol{x}_{ij}\right) = \nu_y t_{ij}\left(\boldsymbol{x}_{ij}\right) \tag{3.16}$$

with transit fees included in the origin-destination cost. When transit uses the same links as other vehicles, such as with many buses, travel time depends on total vehicular flow. Transit could also be given separate links with different travel time functions. Based on the cost per link, the cost of a transit trip is then

$$C_{rs}^{y,\mathrm{TR}}\left(\pi\right) = \varsigma_{rs}^{\mathrm{TR}} + \sum_{(i,j)\in\pi} c_{ij}^{y,\mathrm{TR}}\left(\boldsymbol{x}_{ij}\right)$$
(3.17)

where $\varsigma_{rs}^{\text{TR}}$ is the transit fee for traveling from r to s. Multimodal routes are not permitted in this model.

3.3 Model formulation

The commonly used four-step model is modified to incorporate AV round trips. The latter three steps incorporate a feedback element for convergence to a stable solution. The following subsections discuss each step in greater detail. Multiclass traffic assignment is formulated in Section 3.4.4.

3.3.1 Trip generation

The first step is trip generation, which determines productions \mathbf{P}_r and attractions \mathbf{A}_s based on survey data for each $r \in Z$, $s \in Z$, where Z is the set of zones. Productions and attractions for each zone are vectors in $\mathbb{R}^{|Y|}_+$ to distinguish between VOT classes. Although the distribution among VOT classes may vary at each zone, system-wide consistency of $\sum_{r \in Z} \mathbf{P}_r = \sum_{s \in Z} \mathbf{A}_s$ is required.

3.3.2 Trip distribution

Trip distribution uses a gravity model to determine the number of person trips d_{rs} between every OD pair $(r, s) \in Z^2$, which is assumed to increase with productions and attractions and decrease with travel cost. As with trip generation, $d_{rs} \in \mathbb{R}^{|y|}_+$ to distinguish between VOT class. Minimum cost used for determining person-trips is defined as

$$C_{rs}^{y} = \begin{cases} \min\{C_{rs}^{y,\text{PK}}, C_{rs}^{y,\text{TR}}, C_{rs}^{y,\text{AV}}\} & \text{if } \xi_{\text{AV}}^{y} = 1\\ \min\{C_{rs}^{y,\text{PK}}, C_{rs}^{y,\text{TR}}\} & \text{otherwise} \end{cases}$$
(3.18)

Then

$$d_{rs}^y = \eta_r^y \mu_s^y P_r^y A_s^y \phi\left(C_{rs}^y\right) \tag{3.19}$$

where $\phi(\cdot)$ is a decreasing friction function, $\eta_r^y = \frac{1}{\sum\limits_{s \in \mathbb{Z}} \mu_s^y A_s^y \phi(C_{rs}^y)}$, and μ_s^y is adjusted iteratively to $\frac{1}{\sum\limits_{r \in \mathbb{Z}} d_{rs}^y}$ for consistency with productions and attractions, $\sum\limits_{r \in \mathbb{Z}} \mathbf{P}_r = \sum\limits_{s \in \mathbb{Z}} \mathbf{A}_s = \sum\limits_{r \in \mathbb{Z}} \sum\limits_{s \in \mathbb{Z}} d_{rs}$.

3.3.3 Mode choice

Mode choice splits the person trips per origin-destination into mode-specific trips d_{rs}^m per mode $m \in M$, with M the set of all modes. Travelers may choose between parking, repositioning, and transit. Mode splits are determined by a nested logit model on utility of each mode. To include the benefits of having a vehicle parked at the destination for immediate departure on short notice, an AV preference constant ψ^{AV} is included. ψ^{TR} denotes the traveler preference for transit.

Mode-specific trips per class are therefore defined as

$$d_{rs}^{y,\mathrm{TR}} = \begin{cases} \frac{\exp\left(\psi^{\mathrm{TR}} - C_{rs}^{y,\mathrm{TR}}\right)}{\exp\left(\min\left\{\psi^{\mathrm{AV}} - C_{rs}^{y,\mathrm{AV}}, -c_{rs}^{y,\mathrm{PK}}\right\}\right) + \exp\left(\psi^{\mathrm{TR}} - c_{rs}^{y,\mathrm{TR}}\right)} & \text{if } \xi_{\mathrm{AV}}^{y} = 1\\ \frac{\exp\left(\psi^{\mathrm{TR}} - C_{rs}^{y,\mathrm{TR}}\right)}{\exp\left(-c_{rs}^{y,\mathrm{PK}}\right) + \exp\left(\psi^{\mathrm{TR}} - c_{rs}^{y,\mathrm{TR}}\right)} & \text{otherwise} \end{cases}$$
(3.20)

$$d_{rs}^{y,\text{AV}} = \begin{cases} \frac{\exp\left(\psi^{\text{AV}} - C_{rs}^{y,\text{AV}}\right)}{\exp\left(\psi^{\text{AV}} - C_{rs}^{y,\text{AV}}\right) + \exp\left(-c_{rs}^{y,\text{PK}}\right)} & \text{if } \xi_{\text{AV}}^{y} = 1\\ 0 & \text{otherwise} \end{cases}$$
(3.21)

$$d_{rs}^{y,\text{PK}} = d_{rs}^y - d_{rs}^{y,\text{TR}} - d_{rs}^{y,\text{AV}}$$
(3.22)

To model return trips, additional demand is added for AV round-trips:

$$d_{sr}^{0,\mathrm{AV}} = \sum_{y \in Y} d_{rs}^{y,\mathrm{AV}} \tag{3.23}$$

3.3.4 Traffic assignment

The traffic assignment formulation is multi-class because of the distinction between AV and non-AV vehicles. Marcott and Wynter (2004) demonstrated that multi-class formulations are not necessarily convex despite monotonicity of the travel time function with respect to the flow of any single class. Non-convexity can result in the existence of multiple equilibria as well as non-convergence of algorithms designed for convex objective functions. The weaker convexity requirement they develop of partial nested monotonicity, in general, requires the specification of the optimal link flows of one class as a function of link flows of second class. This is difficult for city-size networks that this model is designed for. Even if these functions were determined, the somewhat arbitrary nature of the VOT parameter could prevent partial nested monotonicity in general, as shown by Marcott and Wynter (2004)'s example network with three equilibria.

Nevertheless, this issue is not unique to this model, but common to all models incorporating multiple discrete VOT classes. Numerical results in section 5 suggest that using the Frank-Wolfe algorithm specified in equation (3.26) as a heuristic for the VI of equation (3.24) converges to an equilibrium, although multiple equilibria are certainly possible. However, we note that many dynamic traffic assignment models, although widely accepted, also cannot be shown to have uniqueness or existence of user equilibria (Chiu et al., 2011).

Multiclass user equilibrium assignment with fixed demand was formulated as a variational inequality (VI) in the form of Nagurney and Dong (2002). Let $\tilde{\boldsymbol{x}} = \{x_1^1, ..., x_{|E|}^1, ..., x_1^{|Y|}, ..., x_E^{|Y|}\}$ be the vector of all class link flows, where E is the set of links. The VI problem is to find $\tilde{\boldsymbol{x}}^* \in \mathcal{K}$ such that

$$\sum_{(i,j)\in E} \boldsymbol{c}_{ij}^{\mathrm{DR}}\left(\tilde{\boldsymbol{x}}^*\right) \cdot \left(\tilde{\boldsymbol{x}} - \tilde{\boldsymbol{x}}^*\right) \ge 0 \tag{3.24}$$

where c_{ij}^{DR} is the vector of class-specific driving costs and \mathcal{K} is the feasible region

defined by

$$\boldsymbol{x}_{ij} = \sum_{\pi \in \Pi} \delta_{ij}^{\pi} \boldsymbol{h}_{\pi} \qquad \forall_{(i,j) \in E}$$
$$\boldsymbol{h}_{\pi} \ge \boldsymbol{0} \qquad \forall_{\pi \in \Pi}$$
$$\boldsymbol{d}_{rs}^{\mathrm{DR}} + \boldsymbol{d}_{rs}^{\mathrm{AV}} = \sum_{\pi \in \Pi_{rs}} \boldsymbol{h}_{\pi} \qquad \forall_{(r,s) \in Z^{2}}$$
(3.25)

The Frank-Wolfe algorithm is used as a heuristic to solve this VI. The step size of λ is found by solving

$$\sum_{(i,j)\in E} \sum_{y\in Y} c_{ij}^{y} \left(\lambda \boldsymbol{x}_{ij}^{*} + (1-\lambda) \, \boldsymbol{x}_{ij}\right) \left(x_{ij}^{y\,*} - x_{ij}^{y}\right) = 0 \tag{3.26}$$

where \boldsymbol{x}^* is the search direction for λ . This appears to converge for a city-size network, as shown in Figure 3.2. The algorithms for multiclass VI formulations of traffic assignment studied by Nagurney and Dong (2002) and Marcott and Wynter (2004) may improve convergence. Optimal convergence of traffic assignment is not a major focus of this study, and a specific algorithm is not a requirement of the model.

3.3.5 Feedback algorithm

The standard four-step algorithm with feedback as described in McNally (2008) is used. Productions and attractions, the output of are trip generation, are assumed to be known. The latter three steps are performed in a feedback loop for convergence. Trip distribution determines total person trips per origin-destination pair and VOT class based on travel costs (initially free flow costs). Mode choice splits person trips into mode-specific trips using a nested logit model. Traffic assignment finds the routes for all vehicle trips, assuming user equilibrium behavior. As the assignment changes based on the personal vehicle trips, the feedback loop allows trip distribution and mode choice to be updated using the travel costs from the traffic assignment.

To improve convergence, the method of successive averages (MSA) algorithm is used for the four-step feedback. Let $d_{rs}(n)$ be the person-trips and $d_{rs}^m(n)$ be the trips using mode $m \in M$ from $r \in Z$ to $s \in Z$ at iteration n of the feedback loop, and $d_{rs}^*(n+1)$ and $d_{rs}^{m*}(n+1)$ be the search direction at iteration n+1. A step size of $\frac{1}{n+1}$ is used, i.e.

$$\boldsymbol{d}_{rs}(n+1) = \frac{1}{n+1} \boldsymbol{d}_{rs}^{*}(n+1) + \frac{n}{n+1} \boldsymbol{d}_{rs}(n)$$
(3.27)

$$\boldsymbol{d}_{rs}^{m}(n+1) = \frac{1}{n+1} \boldsymbol{d}_{rs}^{m*}(n+1) + \frac{n}{n+1} \boldsymbol{d}_{rs}^{m}(n)$$
(3.28)

Convergence was measured based on the root mean squared error of modespecific trips, as suggested by Boyce et al. (1994):

$$RMSE^{d} = \sqrt{\frac{\sum_{r \in Z} \sum_{s \in Z} \sum_{y \in Y} \sum_{m \in M} \left(d_{rs}^{y,m} \left(n + 1 \right) \right) - d_{rs}^{y,m} \left(n \right) \right)^{2}}{|Z^{2} \times Y \times M|}$$
(3.29)

3.4 Numerical results

This section presents results on the downtown Austin network, 2 hour AM peak. Although the model is computationally tractable for a larger network, the size of this network allowed study of multiple scenarios with high detail in analyses. First, the empirical convergence is presented. Then, the effects of increasing AV ownership on transit ridership, repositioning trips, and total personal-vehicle demand are studied.

3.4.1 Description of experiments

The model was tested on the Austin downtown sub-network with 2 hour AM peak trip data provided by the Capital Area Metropolitan Planning Organization. Bus routes are included and were used for transit options. In addition, walking at the speed of 3 mph was permitted along all links for connecting to transit because some zones are not directly served by bus. Although no distance constraint was included due to the complexity imposed on the shortest path algorithm, walking long distances would have a high penalty in travel time with respect to vehicular travel. Altogether, the network has 88 zones, 634 nodes, 1574 links, 62,836 trips, and 84 bus routes, as shown in Figure 3.1.



Figure 3.1: Downtown Austin network

Due to lack of VOT distribution data per zone, the same distribution (shown in Table 3.1) was used for each zone, with VOTs ranging from 1.15 to 22 in units of dollars per hour. Values of time were uniformly chosen from a range based on scaling an income distribution, and the log-normal expression with mean $\mathbb{E}[\nu]$ and standard deviation σ_{ν}

$$\mathscr{P}(\nu) = \frac{1}{\nu\sqrt{2\pi\sigma_{\nu}}} \exp\left(-\frac{1}{2}\left(\frac{\left(\ln\left(\nu\right) - \overline{\nu}\right)^{2}}{\left(\sigma_{\nu}\right)^{2}}\right)\right)$$
(3.30)

was used to determine the class distribution of demand, as suggested by Yang and Meng (2001) and Huang and Li (2007). As shown in Table 3.1, the chosen range accommodates most variation in the distribution. The demand data did not include

Class	VOT (/hr)	Proportion
1	1.15	0.08
2	3.5	0.37
3	5.85	0.28
4	8.15	0.14
5	10.5	0.07
6	13	0.03
7	15	0.015
8	17.5	0.007
9	20	0.004
10	22	0.002

 Table 3.1:
 Value-of-time distribution

trip purpose. Since the data are for the AM peak, all trips are assumed to be for home-based work travel. Price may have different effects on commercial travel or other types of personal trips. The inverse friction function $\phi(C) = \frac{1}{C}$ was used in trip distribution and mode choice. Parking costs were estimated at \$5.00 per day for all zones because more specific data was not available. Although downtown parking fees are often much higher, for long term planning travelers are assumed to have the option of cheaper annual parking passes. Fuel cost was set at \$3.00 per gallon.

On initial availability for public use, AVs may have a high purchase cost because of the novelty of the technology. As production increases, the cost is expected to reduce so that AVs are more affordable. The assumption was made that higher income travelers also have higher VOT, and that income affects affordability of AVs. Therefore, the experiment simulated the entry of AVs into public use by sorting Yin decreasing order by ν_y , and running |Y| + 1 experiments. On the nth experiment, the first n-1 classes of this ordering of Y were assumed to use autonomous vehicles.

3.4.2 Convergence of static traffic assignment

Because of the multi-class formulation, the traffic assignment VI does not necessarily have a unique or even existent equilibrium (Marcott and Wynter, 2004), and



Figure 3.2: Convergence of traffic assignment

therefore the commonly used Frank-Wolfe algorithm is not guaranteed to converge. However, empirical results of running Frank-Wolfe on the downtown Austin network suggest that it converges to an equilibrium. Figure 3.2 shows convergence for the case in which the 8 highest VOT classes 55% of the demand use AVs. Convergence is measured through the average excess cost, i.e. the average difference between observed and shortest path travel costs. Similar convergence was observed for all scenarios in the gradual availability of AVs experiment.

3.4.3 Autonomous vehicle demand

Figure 3.3 shows the decrease in transit demand as more VOT classes receive access to AVs. Transit demand is high without AVs because a high proportion of low VOT travelers, which are the majority of the demand (see Table 3.1), choose transit. The pattern of decrease roughly follows the class proportions because the reduction in transit utility is primarily due to the lower cost of AVs. When AVs are available only to the upper classes, which comprise a small fraction of the population, the effect is small. However, as autonomous vehicles become available to lower-middle VOT



Figure 3.3: Total transit demand

classes, the rate of decrease in transit demand is much greater. Overall, the model predicts a reduction in transit ridership of 61.4% due to lower costs of AVs for low VOT travelers (see Tables 3.2 and 3.3). AV round-trip demand was a high fraction of the total personal vehicle demand, reaching 83% at full market penetration (Figure 3.4). This analysis also neglected the possible reduction in parking fees due to the economics of lower demand. However, because the alternative is a return trip, parking costs would likely need to be significantly lower to be competitive against the fuel cost of a return trip to the origin.

Similarly, for transit to be competitive against AVs, transit must provide benefits in cost or travel time. Transit costs in this model were \$1, so a reduction in cost sufficient to be competitive against the lack of parking costs would be difficult. However, restricted-access routes for transit such as bus rapid transit or metro could provide advantages in travel time.



Figure 3.4: Autonomous vehicle round-trip demand as a percentage of total personal vehicle demand

3.4.4 Long-term effects

Table 3.2 shows the mode split for each VOT class before any AVs and after full AV availability, and Table 3.3 shows the mode costs per class. Total demand for any personal vehicle mode changed from 23,500 person trips to 47,676 trips, and with the shift to 39,592 AV round-trips, the total number of trips made by personal vehicles increases to 87,275 an increase of 271.4%. Although many of these additional trips are traveling away from downtown, the network still experiences significant increases in link volume. However, average speed decreases are modest, as shown in Figure 3.5. This is encouraging because it suggests that the increases in demand are substantially offset by increases in capacity from AVs.

3.4.5 Effect on traffic congestion

Figure 3.5 shows that average link travel speeds mirrors the class proportions, indicating that the decrease in average link speeds is due to the switch to AV round-

 Table 3.2: Comparison of mode-specific demand before and after autonomous vehicle

 availability

Class	Demand without AVs		Demand with AVs			
	Park	Transit	Round-trip	Park	Transit	Round-trip
1	3.10%	96.90%		1.40%	49.00%	49.60%
2	15.20%	84.80%		6.10%	33.00%	60.90%
3	41.40%	58.60%		15.10%	19.60%	65.40%
4	64.10%	35.90%		20.90%	12.00%	67.10%
5	78.90%	21.10%		24.30%	7.80%	67.80%
6	88.00%	12.00%		26.60%	5.30%	68.10%
7	92.30%	7.70%		27.80%	3.90%	68.20%
8	95.50%	4.50%		28.90%	2.80%	68.30%
9	97.30%	2.70%		29.60%	2.10%	68.30%
10	98.20%	1.80%		30.00%	1.70%	68.20%

 Table 3.3: Comparison of mode and class specific costs (in dollars) before and after

 autonomous vehicle availability

Class	Cost without AVs			Cost with AVs		
	Park	Transit	Round-trip	Park	Transit	Round-trip
1	5.94	2.04	2.67	6.05	1.99	0.57
2	6.06	3.85	2.58	6.33	3.75	0.79
3	6.2	5.73	2.6	6.63	5.54	1.01
4	6.34	7.66	2.67	6.92	7.31	1.22
5	6.48	9.64	2.71	7.23	9.13	1.44
6	6.64	11.72	2.73	7.56	11.08	1.67
7	6.75	13.38	2.73	7.82	12.63	1.86
8	6.9	15.42	2.73	8.15	14.56	2.09
9	7.04	17.45	2.73	8.47	16.49	2.33
10	7.16	19.06	2.73	8.73	18.04	2.52



Figure 3.5: Change in average link speed, weighted by length, as autonomous vehicle availability increases

trips. On the north/south bound freeways and arterials, much of the AV round-trip traffic travels in the opposite direction away from workplaces in downtown. Within the downtown grid itself, AV round-trips contribute to congestion while leaving the area. However, the changes are relatively small, suggesting that roadway capacity increases negate some of the additional vehicular travel demand. Average link speeds may be higher than expected because of the lack of intersection penalties which are a major factor in the downtown region. Modeling the reduced intersection penalties due to TBR controls is the subject of Chapter 5.

3.5 Conclusions

This chapter developed a model to analyze the impact of AV availability on AM peak transit demand. AVs allow the option of a drop-off and return trip to avoid parking costs, incurring only additional fuel consumption, so a generalized cost function of travel time, monetary fees, and fuel was created to model the cost of a

trip. On the other hand, AV use increases road capacity, reducing travel times. This inspired a jam density function of the proportion of AVs on the road, with capacity assumed to be a linear function of jam density in accordance with Greenshield's (1935) speed-density relationship. The resulting travel time function was proven to be monotone increasing for the specific jam density function used. This generalized cost function and AV round-trip mode was incorporated into a multi-class four-step planning model, and convexity of the user equilibrium traffic assignment objective function was shown. The model was tested on the Austin downtown network including its bus routes. Results indicated that parking cost was a main incentive for transit, and that avoidance of parking costs through AV round-trips resulted in both an increase in AV round-trips relative to one-way and park trips and a decrease in transit demand. However, only modest increases in average link speed were observed. These are likely due to two factors: first, AVs have a reduced following headway resulting in higher capacity, which is included in the travel time function; second, most repositioning trips are away from downtown, whereas most traveler trips are moving towards downtown, so they use somewhat different links.

Since AVs are likely to initially be more expensive, and therefore affordable only for upper-class travelers, transit authorities have a period between introduction of AVs and high reduction of transit demand. Transit authorities may benefit from developing restricted-access routes for transit because the mode switch to AV roundtrips will result in additional road congestion. The experiments in this paper modeled a city with bus routes that share roads with personal vehicles. Cities with metro or bus rapid transit may observe a smaller reduction in transit demand due to the increase in personal vehicle travel times. Higher congestion also increases fuel consumption, which may be an incentive for lower VOT travelers to switch to transit.

The ultimate goal is for this planning model be extended to DTA to more accurately model the traffic impact of greater capacity, and to include the improvements of AV intersection controls such as TBR. However, first DTA must be integrated into the four-step model. Then, TBR must be modified to be computationally tractable for DTA. These developments occur in Chapters 4 and 5, respectively, and lead to the four-step planning with DTA and AV behavior in Chapter 6.

4 INTEGRATING DYNAMIC TRAFFIC ASSIGNMENT INTO FOUR-STEP PLANNING WITH DEPARTURE TIME CHOICE

4.1 Introduction

Using DTA instead of STA in four-step planning offers several advantages. Foremost for this thesis is the possibility of greater accuracy in modeling AV intersection dynamics. In addition, many practitioners still use the STA four-step model, and are interested in incorporating DTA into their planning analyses. The DTA four-step model developed here may be of benefit to them. To make full use of the time index in DTA demand and travel time predictions, trip distribution and mode choice are modified to include departure time. This results in an endogenous departure time profile for DTA vehicle demand.

4.1.1 Motivation

Although the more aggregate STA can model certain aspects of AV behavior, such as link capacity improvements and repositioning trips, other advantages such as TBR vary depending on specific intersection demand. An average intersection capacity of TBR could be included in STA but has not been studied in the literature. Since the greater detail in DTA results in greater accuracy in the traffic flow model, this thesis integrates DTA into four-step planning then adds AV flow and trip behaviors.

In addition to predicting the impacts of AV intersection dynamics, planning tools for forecasting future conditions are essential to transportation science. Modeling these conditions with a high level of accuracy allows implementing corrective or advantageous system changes in advance. Initial models were based in static traffic assignment and assumed steady-state conditions. However, in reality demand varies over time due to variations in departure time choice among travelers. Time-varying trip departure times and travel times in DTA not only provide more realistic traffic behavior but may also offer the possibility of enhancing the planning process.

Traditionally, the four-step travel demand model has been used to forecast conditions. The final step, traffic assignment, typically involves the use of a STA model, where link performance functions represent the average or steady state traveltime on a link as a function of the volume of traffic on that link. However, there are a number of limitations induced by properties of link performance functions, including the lack of queue propagation and the absence of time-of-day differences.

The modeling disadvantages in STA and the increasing availability of efficient software programs and improved computer architecture have made DTA a potentially valuable tool for transportation planning agencies. According to a recent survey conducted by the Federal Highway Administration, 90% of respondents, mainly consisting of government agencies and consulting firms, want to incorporate DTA into their planning analyses in three to four years at the latest (Chiu, 2010). Furthermore, 65% of the respondents planned to eventually replace their existing STA model with DTA.

However, many current DTA models use a universal departure time profile. Previous work on integrating DTA into planning models (Tung et al., 2010; Pool et al., 2012; Duthie et al., 2013) modified only the inputs and outputs of traffic assignment to replace STA with DTA. Vovsha et al. (2012) used a time-dependent mode choice step but still used an exogenous demand profile to distribute trips over possible departure times. Determining the distribution of vehicle departure times is one of the most significant challenges for DTA planning models (Peeta and Ziliaskopoulos, 2001).

Other studies (Ziliaskopoulos and Rao, 1999; Friesz et al., 2001; Szeto and Lo, 2004; Bliemer et al., 2010) have explored simultaneous route and departure time choice that determines a profile for short-term travel choices. Bellei et al. (2006) created a long-term choice-based model based on a departure time penalty and arc performance functions. The integration with the four-step model proposed here admits general DTA models for long-term planning choices such as residence and job location. Another approach to using DTA for planning could be to integrate DTA with an activity-based model (Lin et al., 2008). However, the additional detail in inputs may be too costly for many agencies that have been using the traditional fourstep model since the early 1960s. Therefore, combining the traditional model with DTA may be the best immediate approach to add detailed temporal traffic dynamics to existing long-term planning processes.

4.1.2 Contributions

To create an endogenous, origin-destination specific departure time distribution of home-to-work trips for long-term planning, this thesis proposes a trip distribution based on a gravity model with an arrival time penalty function for departure time choice. The arrival time penalty is based on a desired arrival time per OD. The resulting demand is greatest at departure times that will result in arriving near the desired arrival time. The time index in trip distribution also accounts for time-varying travel times from DTA. Empirical results are verified to perform as expected for a single desired arrival time on the downtown Austin city network. Finally, a study using a distribution of desired arrival times demonstrates the flexibility of the model.

The remainder of this chapter is organized as follows: Section 4.2 presents the departure time choice model and incorporates it along with DTA into the four-step planning model with feedback. The model is compared with four-step with STA and a time-aggregation DTA integration on a city network in Section 4.3, followed in Section 4.4 by an analysis of convergence and differences in the resulting trip tables and mode choice. Empirical results demonstrate significant differences in time-varying trips and travel times that could have major impacts on network analyses relying on these planning processes. Section 4.5 discusses conclusions of the DTA four-step model.

4.2 Departure time choice from arrival time penalty

We first introduce the arrival time penalty in Section 4.2.1. Section 4.2.2 gives a brief review of the traditional four-step planning model, and modifications are

presented in Section 4.2.3. Sections 4.2.4 and 4.2.5 discuss solution methods.

4.2.1 Arrival time penalty

A generalized cost function incorporating an arrival time penalty for the morning commute was introduced by Vickrey (1969). For simplicity, each origin-destination pair (r, s) is assumed to have some preferred arrival time T_{rs}^{pref} . Although Vickrey's (1969) model assumed that all travelers have the same desired arrival time, the OD index requires only that all travelers from an origin to a destination have the same T_{rs}^{pref} . This admits more general arrival time preference distributions, such as a single desired arrival time per workplace that Szeto and Lo (2004) assumed.

Early and late arrival are respectively penalized by β and γ cost units per unit time. Travel time t_{rst} from r to s for trips departing at t is weighted by α to create a generalized cost C_{rs}^{PK} for driving trips and C_{rs}^{TR} for transit trips. (This chapter does not consider autonomous vehicle repositioning trips.)

$$C_{rst}^{\rm PK} = \alpha t_{rst}^{\rm PK} + \beta \max\{0, T_{rs}^{\rm pref} - (t_{rst}^{\rm PK} + t)\} + \gamma \max\{0, t_{rst}^{\rm PK} + t - T_{rs}^{\rm pref}\} + \varsigma_s^{\rm PK}$$
(4.1)

$$C_{rst}^{\mathrm{TR}} = \alpha t_{rst}^{\mathrm{TR}} + \beta \max\left\{0, T_{rs}^{\mathrm{pref}} - \left(t_{rst}^{\mathrm{TR}} + t\right)\right\} + \gamma \max\left\{0, t_{rst}^{\mathrm{TR}} + t - T_{rs}^{\mathrm{pref}}\right\} + \varsigma_{rst}^{\mathrm{TR}} \quad (4.2)$$

where $\varsigma_{rst}^{\text{TR}}$ is the transit fee for traveling from r to s departing at t on transit. Note that avoidance of parking costs through AV repositioning trips are not included in this chapter, so the driving mode is denoted by PK. The assumption $\beta < \alpha < \gamma$ is made to prevent cyclical routes which might occur if arriving early was more onerous than traveling. In reality, arrival time preference and importance is likely to vary by traveler as well as by workplace. For instance, Newell (1987) studied arrival time preference distributions, and Caplice and Mahmassani (1992) collected data on how many minutes before the start of work travelers prefer to arrive at the workplace. However, we take the assumption of a common arrival time per OD to simplify the coupling of departure time choice and trip distribution, an assumption which should be relaxed in future work.

The generalized cost is used within a time-indexed modification trip distribution in the traditional four-step planning model to select departure times. A brief review of the four-step model is given below, followed by the modifications to incorporate departure time choice.

4.2.2 Traditional four-step model

McNally (2008) provides a formal description of and discussion on the developmental history of the four-step planning model. The steps are mentioned below to introduce the modifications incorporated to add departure time choice. Figure 4.1 shows the four steps as well as the modifications.

Trip distribution is typically a gravity model for determining person trips of d_{rs} from r to s. The gravity model assumes that the number of trips decreases as travel cost increases. Trips are proportional to the productions P_r , attractions A_s , (time-independent) travel cost C_{rs} , and some decreasing function $\phi(\cdot)$:

$$d_{rs} = \eta_r \mu_s P_r A_s \phi\left(C_{rs}\right) \tag{4.3}$$

where

$$\eta_r = \frac{1}{\sum_{s \in Z} \mu_s A_s \phi(C_{rs})} \tag{4.4}$$

and μ_s is adjusted iteratively to

$$\mu_s = \frac{A_s}{\sum\limits_{r \in Z} d_{rs}} \tag{4.5}$$

Mode choice determines the proportion of person trips using the driving mode, p_{rs}^{PK} , to find vehicle trips $p_{rs}^{PK}d_{rs}$. Because AVs are not studied in this chapter, the only mode options are to drive and park or take transit. An optimization framework for trip distribution and mode choice can be found in Sheffi (1985). These steps are performed iteratively as shown in Figure 4.1 to respond to changing travel times.

Replacing STA with DTA introduces two data conversion issues due to the time-invariant nature of the four-step process and the time-varying inputs and outputs of DTA. First, the vehicle trip table must be distributed over time for input into DTA.



Figure 4.1: Proposed changes to the four-step planning model

This typically uses an external, origin-destination independent, fixed distribution profile. A uniform distribution is one possibility, although more information may lead to more realistic choices, such as a bell curve. Second, the time-varying travel times of DTA must be aggregated for feedback into trip distribution and mode choice. A departure time choice model, such as the one proposed in this thesis, can address these issues and incorporate the time index of the DTA output into the feedback.

4.2.3 Time-varying four-step model

The traditional four-step model described in Section 4.1 distributes trips over origin-destination pairs but does not specify departure time. Previous integrations of DTA into the planning model (Tung et al., 2010; Pool et al., 2012; Vovsha et al., 2012; Duthie et al., 2013) have used a universal, exogenous demand profile to distribute the trips over time for input to DTA. This modification of the trip distribution and mode choice steps obviates the need for an arbitrary time distribution, although it assumes departure time and trip choice depend only on productions, attractions, and timevarying costs, without the influence of external pressures such as work start and end times. While an activity-based model can alleviate these issues, the additional detail in inputs and model, higher computation time, and widespread use of four-step suggest that a four-step modification may be valuable for practitioners. The following model (shown in Figure 1) uses the arrival time penalty function to select a departure time from a set of discrete assignment intervals \mathcal{T} in trip distribution.

Although departure time choice may be considered a shorter-term decision than residence or office locations, those choices are influenced by travel time, which varies with departure time. Since departure time choice affects trips because of timevarying travel times, the gravity model is modified to perform both choices simultaneously. This assumes time-varying trips are proportional to the friction function $\phi(\cdot)$ with input time-varying generalized travel cost from equation (4.1). Doubly constrained trip distribution is defined by the following:

$$d_{rst} = \eta_r \mu_s P_r A_s \phi\left(C_{rst}\right) \tag{4.6}$$

Similarly to equation (4.4), η_r is adjusted to

$$\eta_r = \frac{1}{\sum_{s \in \mathbb{Z}} \sum_{t \in \mathcal{T}} \mu_s A_s \phi\left(C_{rst}\right)}$$
(4.7)

which results in

$$\sum_{s \in Z} \sum_{t \in \mathcal{T}} d_{rst} = \sum_{S \in Z} \sum_{t \in \mathcal{T}} \frac{\mu_s P_r A_s \phi(C_{rst})}{\sum_{s' \in Z} \sum_{t' \in \mathcal{T}} \mu_{s'} A_{s'} \phi(C_{rs't'})} = P_r$$
(4.8)

As with equation (4.5), μ_s is adjusted iteratively to

$$\mu_s = \frac{A_s}{\sum\limits_{r \in \mathcal{I}} \sum\limits_{t \in \mathcal{T}} d_{rst}}$$
(4.9)

Equations (4.7) and (4.9) ensure that the totals of time-varying trips are consistent with aggregated productions and attractions.

Mode choice is typically a function of mode specific costs. As suggested by Vovsha et al. (2012), mode choice can be performed per $t \in \mathcal{T}$ using time-varying costs as input to determine p_{rst}^{PK} , the proportion of trips from r to s departing within t using the drive alone and park mode.

Because the modified trip distribution and mode choice include a time index, DTA is used directly. Vehicle trips, determined by mode choice, are the demand for DTA, and time-varying travel times predicted by DTA are used as input to trip distribution.

4.2.4 Convergence criteria

To gain an understanding of how the new four-step model performs over multiple iterations, it is necessary to develop some criteria to measure convergence. As suggested by Boyce et al. (1994), the root-mean squared error was used to measure changes in trip tables. For trips, it is defined as follows:

$$RMSE^{d} = \sqrt{\frac{\sum\limits_{(r,s,t)\in(Z^{2}\times\mathcal{T})}\sum\limits_{m\in M}\left(d_{rst}^{m}\left(i+1\right)-d_{rst}^{m}\left(i\right)\right)^{2}}{|Z^{2}\times\mathcal{T}\times M|}}$$
(4.10)

where $d_{rst}(i)$ is d_{rst} at iteration *i* of the four-step process. Although a gap function could be a more useful measure of convergence, convergence of integrated planning and DTA models is still an open area of research, and more work is needed to determine an appropriate gap function.

The average excess cost from the traffic assignment sub-problem evaluates the quality of the travel time output of traffic assignment used as feedback. Travel times from a solution with high excess cost may be more unrealistic. For DTA, excess cost was defined as a percentage of the total system travel time

$$G = \frac{\sum\limits_{\substack{(r,s,t)\in(Z^2\times\mathfrak{T})\\(r,s,t)\in(Z^2\times\mathfrak{T})}} (t_{rst} - t_{rst}^*) d_{rst}}{\sum\limits_{\substack{(r,s,t)\in(Z^2\times\mathfrak{T})}} t_{rst} d_{rst}}$$
(4.11)

where t_{rst}^* is the shortest path travel time from r to s departing at t. At DUE, G = 0, but in practice, both static and dynamic traffic assignment are typically solved only to an acceptable level of excess cost.

4.2.5 Method of successive averages

The method of successive averages (MSA), described for the four-step feedback process by Boyce et al. (1994) and studied by Guo et al. (2010), is often used to improve convergence in practice. Instead of using the output of trip distribution and mode choice directly, an average is taken of the old trip table and the new table with decreasing weight as iteration increases. Denote by $p_{rst}^{\rm PK}(n)$ the proportion of trips from r to s departing at t choosing the driving mode at iteration n. Formally, for the time-aggregation framework, after determining $d_{rst}(n+1)$ person trips from trip distribution and $p_{rst}^{\rm PK*}(n+1)$ driving proportion from mode choice for trips from r to s departing at t for iteration n + 1, MSA uses

$$d_{rst}(n+1) = \frac{1}{n+1} d_{rst}^*(n+1) + \frac{n}{n+1} d_{rst}(n)$$
(4.12)

$$p_{rst}^{\rm PK}(n+1) = \frac{1}{n+1} p_{rst}^{\rm PK*}(n+1) + \frac{n}{n+1} p_{rst}^{\rm PK}(n)$$
(4.13)

for the actual person trips and driving proportions.

4.3 Case study

This section discusses a case study on the downtown Austin city network to analyze differences between the two frameworks. The network has 152 zones, 549 intersections, 1261 directed links, and 88,850 trip productions in the 2-hour morning peak period. Total demand levels were varied to analyze convergence in more general scenarios, as demand is likely to change in future planning models. Trip productions were based on data from the Capital Area Metropolitan Planning Organization and scaled according to the scenario. Scenarios of 80%, 90%, 100%, 110%, and 120% of the base productions were tested for sensitivity analyses. Traffic signal data was given by the City of Austin.

The four-step model feedback algorithm shown in Figure 1 was implemented with travel times updated from the output of traffic assignment each iteration. Initially, free flow travel times were used for t_{rst} . Trip distribution used the gravity models described by equations (4.6) through (4.9) with friction factors of

$$\phi\left(C\right) = \frac{1}{C} \tag{4.14}$$

The inverse friction function was chosen for demonstration purposes. However, other functions, such as an exponential deterrence function, are compatible and could be used instead. For the modified friction function with arrival time penalties described by equations (4.1) and (4.2), $\alpha = 1$, $\beta = 0.609$, and $\gamma = 2.38$ were chosen based on value-of-time values for one of the vehicle classes analyzed by Liu and Nie (2011). Trips were distributed over the morning peak from 7am (t = 0) to 9am. Mode choice used a logit model based on ν , the value of time; ψ^{TR} , the transit bias; and χ , the logit dispersion factor. Parking fees were assumed to be included in the transit bias.

$$p_{rst}^{\rm PK}(n) = \frac{1}{1 + \exp\left(\chi\left(\left(\psi^{\rm TR} - C_{rst}^{\rm TR}(n) + C_{rst}^{\rm PK}(n)\right)\right)\right)}$$
(4.15)

Specific parameters for the logit model were $\psi^{\text{TR}} = -47.6$, $\zeta_{rs}^{\text{TR}} = 1$, and $\chi = 0.0548$, as used by Pool (2012), which assumes a parking fee of \$5 for all zones. MSA (as discussed in section 4.2.5) was applied to trip distribution and mode choice.

4.3.1 Mode options

For travel mode options, buses were added which operate on fixed routes through the traffic network. They affect travel times through interactions with other vehicles but possibly reduce the total number of vehicles on the road. The subset of the Austin bus routes that are contained in the downtown Austin network was encoded, with two minute waiting periods added to travel times. However, multi-modal journeys are not possible, so travelers could only choose bus routes if their origin and destination were both near bus stops.

4.3.2 Traffic assignment

UE in DTA is well defined in previous literature (Lo and Chen, 2000; Lu et al., 2009; Chiu and Bustillos, 2009). The method of successive averages (MSA-TA) solution algorithm was used for convergence. Traffic assignment was equilibrated based on travel times. However, assuming $\beta < \alpha < \gamma$, minimizing travel time also minimizes the arrival time penalty because travelers, after departing, have a lower cost for arriving early than taking a longer route. At iteration *n* of MSA-TA, $\frac{1}{n}$ of the flow is moved to the time-dependent shortest path per origin, destination, and assignment interval. New paths were found for 30 iterations, followed by a further 20 iterations of equilibrating among existing paths. Warm-starting involved assigning vehicles based on the previous flow assignment proportions, then starting MSA-TA from iteration

n = 5 with 5 iterations of finding new paths, then 20 more of equilibrating among existing paths. Travel times were computed using the flow model and simulator of the Visual Interactive System for Transport Algorithms (VISTA) (Ziliaskopoulos and Waller, 2000) based on the cell transmission model introduced by Daganzo (1994, 1995).

To further improve computation time, the traffic assignment output of fourstep iteration n was used as a warm-start to four-step iteration n + 1. This technique was based on Levin et al. (2014a), which found that DTA convergence could be improved through the use of a STA warm-start. Although the trip tables are different each iteration, we assumed that variation is sufficiently small that an assignment for iteration n + 1 based on paths for iteration n is better than starting from free-flow paths. Thus, flow was assigned to routes proportionally based on the flow assignment from the previous iteration. The number of iterations and/or the number of new paths found was correspondingly reduced.

4.4 Numerical results

The results section has two main parts. Sections 4.4.1 through 4.4.3 demonstrate the effect on departure times through a universal arrival time preference of $T_{rs}^{\text{pref}} = 8:45$ am. The purpose of this assumption is to demonstrate that the model produces expected results. These results were compared with three other models, which are described below. Section 4.4.4 then analyzes the model output under a distribution of arrival time preferences. Each destination was assigned a preferred arrival time from a normal distribution with $\mathbb{E}[T] = 8:45$ am and $\sigma_T = 15$ minutes. To conclude the results, Section 4.4.5 discusses computation times on the city network.

4.4.1 Comparison models for verification

To analyze the effect on departure time choice and convergence of the feedback process, the proposed model was compared with three other models in Sections 4.4.1 through 4.4.3. The first of the comparison models is a four-step model using STA as described by Section 4.3.1 and mode choice by equation (4.14) without the time index, using the Bureau of Public Records travel time function:

$$t_{ij} = \hat{t}_{ij} \left(1 + \aleph_{ij} \left(\frac{x_{ij}}{Q_{ij}} \right)^{\beth_{ij}} \right)$$
(4.16)

where \hat{t}_{ij} is the free-flow travel time, \aleph_{ij} and $\exists ij$ are calibration constants, x_{ij} is flow, and Q_{ij} is capacity for link [i, j]. This is representative of the traditional model still in use by many practitioners.

The second model is a *time-aggregated* integration of DTA into the timeinvariant four-step model in Section 4.3.1. Average peak travel times, given by

$$\bar{t}_{rs} = \frac{\sum_{t \in \mathcal{T}} t_{rst}}{|\mathcal{T}|} \tag{4.17}$$

were used for input to time-invariant trip-distribution and mode choice. Departure times were uniformly distributed over the window of 7:00am to 9:00am for the DTA demand. This model is similar to previous work on integrating DTA and the four-step model (Tung et al., 2010; Vovsha et al., 2012; Duthie et al., 2013).

The third comparison model is a time-varying model without the arrival time penalty, i.e. $\alpha = 1$, $\beta = 0$, and $\gamma = 0$). This is to demonstrate the utility of an arrival time preference for the time dimension choice. Without an arrival time penalty, travelers seeking to minimize only travel time are predicted to depart in off-peak times to avoid the heaviest congestion.

4.4.2 Comparison of departure times

For a perspective on the differences in predicted trip tables and travel times, results from the time-aggregated framework using a uniform time distribution profile and the time-varying framework are compared. Average trips in the time-aggregated and time-varying frameworks after a 15 iterations are shown in Figure 4.2. Departure time bins are indexed by the start time, and have a duration of 900 seconds. Despite the initially lower congestion and correspondingly lower travel times shown in Figure 4.3, when time penalties are applied trips peak at the 8:30am assignment interval



Figure 4.2: Average trips per departure time

Time-varying with and without the arrival time preference is compared. Note: Four-step with STA has the same average origin-destination-assignment interval ODT trips as time-aggregate, and is not shown here.

because of the desired arrival time of 8:45am. The average trips differ by 0.1% for the time-varying and time-aggregate cases, but the sum of the absolute differences is 1.31 130.5% of the average trips. That could lead to major differences in results when using the planning model to estimate time-varying network conditions. However, that difference is small when compared to the four-step model using STA. Because of lower predicted travel time (Figure 4.3) due to the lack of a hard capacity and queue spillback, average trips were significantly higher, indicating that 0 trips were predicted for more origin-destination pairs. We refer the reader to Duthie et al. (2012) for a discussion of differences between static and dynamic traffic assignment which might lead to travel time differences. These differences in predicted trip tables illustrate potential planning output improvements by using either DTA framework, particularly when capacity calibration is uncertain. Without an arrival time penalty, shown in Figure 4.2, trips favor departing at t = 0 more than any other interval



Figure 4.3: Average travel times per departure time, weighted by trips

because of the lower initial congestion before many vehicles enter the network. Timevarying costs over the rest of the peak period resulted in only minute differences in the average number of trips, unlike with arrival time penalties.

Average predicted travel times, shown in Figure 4.3, varies inversely with average trips as expected from use of the gravity model. DTA link capacities were used directly in the static model, which resulted in static assignment predicting far lower travel times. The time-aggregate framework also predicted lower average travel times than the time-varying framework. In fact, the total system travel time was 31,939 hours for the time-varying framework but only 10,618.71 hours for the time-aggregate framework. Because of the arrival time penalty, in the time-varying framework more trips depart closer to the preferred arrival time. Because of pre-existing congestion from earlier vehicles yet to exit the network, and the higher number of vehicles entering, a greater number of trips experience higher congestion. However, although not verified against real data, the endogenous trip distribution is likely more realistic because of the influence of arrival time.



Figure 4.4: Average departure time vs. average travel time for each O-D pair

4.4.3 Origin-destination departure time choice

Distribution of trips over time varied significantly by travel time for individual origin-destination pairs. Figure 4.4 plots the average travel time against the average departure time for each O-D pair for the 100% demand case. The distinct downward trend indicates that as travel time increases, trips tend to depart earlier to minimize the arrival time penalty, which is more heavily weighted for arriving late. The only O-D pairs with an average departure time at or above the preferred arrival time of 8:45am are those with a very small travel cost of less than a minute.

To further demonstrate the differences in individual O-D distribution profiles, distribution profiles from two O-D pairs with high differences in travel time are compared. Figure 4.5 shows the trip distribution and time-varying travel times for an O-D pair with travel times averaging around 10 minutes. Most trips depart around 8:30am because of the preferred 8:45am arrival time, even though that is when travel times are highest, to minimize arrival time penalties. In contrast, Figure 4.6 shows an O-D pair with travel time ranging from under 10 minutes to over 30 minutes, with an average around 20 minutes. As a result, most vehicles depart around 8:00am because


Figure 4.5: Trip distribution and travel times for an O-D pair with 10 minute average travel times

of the combination of 20 minute travel time and the asymmetric arrival time penalty. Few trips depart at 8:30am because of congestion-induced 30 minute travel times and higher penalties for arriving late.

4.4.4 Convergence of four-step model

Convergence of the four-step process is demonstrated in Figures 4.7 and 4.8, which show the root mean squared error in trip tables from the previous iteration. The time-aggregated framework converged more slowly, and with less stability at higher demand scales, than the time-varying framework. A contributing factor is the addition of departure time choice rather than the assumption of a uniform distribution over time. Departure time choice from the gravity model should result in smaller travel time variations as the trips are tailored to time-varying rather than averaged travel times. The time-varying framework avoids this by adjusting the trips at each assignment interval to an appropriate level, which may explain the faster convergence. In practice, for reduction of computation time, the four-step process could be termi-



Figure 4.6: Trip distribution and travel times for an O-D pair with 20 minute average travel times

nated at an earlier iteration once the difference in trip tables between iterations is below some threshold.

4.4.5 Distribution in preferred arrival times

Having verified the departure time profile for a universal preferred arrival time, results for a distribution of desired arrival times are presented. Preferred arrival time per destination was sampled from a normal distribution with mean of 8:45am and standard deviation of 15 minutes. The resulting overall departure time profile, shown in Figure 4.9, peaked at 8:00am instead of 8:30 am for the universal desired arrival time, and appears to decline linearly in either direction. The shape is also somewhat different, as compared with Figure 4.2. Later departure times, such as 8:30am and 8:45am, have fewer trips because only ODs with short travel times and a later desired arrival time choose those departure times. Similarly, early departure times are used primarily by ODs with early arrival times and longer travel times. The peak of 8:00am satisfies trips with longer travel times or with earlier arrival times.



Figure 4.7: Trip table convergence for the time-aggregated framework



Figure 4.8: Trip table convergence for the time-varying framework



Figure 4.9: Overall departure time profile for normally distributed arrival time preferences

Although the overall profile in Figure 4.9 is similar to a bell curve-shape profile often used in practice, the main differences are in the departure times for individual ODs. Figure 4.10 shows the great variation in average departure time between ODs. It vaguely follows an inverse relationship, but includes much greater noise when compared with Figure 4.4. For ODs with short travel times, the high variation in departure time is due to the normal distribution of desired arrival times. As expected, the cluster of ODs with longer travel times, between 3000 and 5000 seconds, departs relatively early to meet arrival time preferences.

Transit demand (shown in Figure 4.11) was initially low when calculated based on free flow travel times, then increased as congestion was included in travel times. This is likely because based on free flow times, most trips chose later departure times, resulting in high congestion near the end of the simulation period. This made the higher travel time due to transits non-direct routes less onerous in comparison. Transit demand then declined over iterations as the model converged to a balance between higher travel time and arrival time penalties. Transit demand overall is fairly



Figure 4.10: Average departure time vs. average travel time for each O-D pair for normally distributed desired arrival time

low because of connectivity limitations in the transit model. The DTA software used made difficult consideration of transit trips with transfers, or trips requiring walking from the transit stop to the destination. However, this does not detract from the formulation, nor from the endogenous departure time profile observed in the results.

4.4.6 Computation time

The four-step frameworks were run on an Intel Xeon X5680 running at 3.33GHz. Computation times were high due to repeated runs of dynamic traffic assignment as a sub-problem, which generally scaled with number of trips. An average of 30.7 hours was required for 15 iterations for the time-varying model. However, the quickly decreasing $RMSE^{d}$ for the time-varying model suggests that a good solution might have been achieved much earlier in the feedback process. Additionally, because this implementation was not multithreaded, a parallel implementation could reduce computation time by a significant factor. Furthermore, the warm-start applied in later iterations reduced the computation time for all but the 100% scale test without a loss



Figure 4.11: Transit demand evolution over four-step iterations (Note: Connectivity issues in the transit data reduced the total transit demand.)

in the quality of the traffic assignment. Advances in technology and algorithms will continue to reduce computation times.

4.5 Conclusions

Trip distribution from the traditional four-step planning model was modified to include departure time choice based on the well-known arrival time penalty function. This model results in endogenous departure time choice dependent on time-varying travel times from DTA and an externally specified arrival time preference per O-D pair. Trips were assumed to correspond inversely to travel times per a gravity model. This trip distribution was incorporated into an integration of DTA with the four-step model including time-varying logit mode choice. Empirical results on a city network demonstrate that O-D specific demand profiles of trips reflect average travel times, verifying that trips are discouraged by penalties from arriving significantly earlier or later than preferred. This corresponds to peak hour congestion, as opposed to travelers departing at off-peak hours to minimize travel time alone. The feedback algorithm of the planning process appears to converge faster when using this timevarying trip distribution than a time-aggregated integration of DTA into the four-step model.

The model in this chapter addresses several issues faced by practitioners seeking to switch from static to dynamic traffic assignment models. In previous work, the time-index of DTA information has been removed through aggregation to allow a simple replacement of static with dynamic. This prevents full use of the flow dynamics present in DTA and requires the assumption of an exogenous demand profile, which is usually defined universally. In creating an endogenous, O-D specific demand profile, this model presents an alternative solution to the integration of DTA into the four-step planning process which makes use of the time-varying information. The additional required input data of work start times at each zone is less difficult to obtain than an OD-specific demand profile. In addition, the endogenous demand profile changes in response to variations in demand for long-term planning scenarios.

By integrating DTA into the four-step model, a planning model including more detailed AV roadway behaviors may be created. The TBR model proposed by Dresner and Stone (2004, 2005) has been shown to reduce intersection delays beyond SYNCHRO-optimized traffic signals (Fajardo et al., 2011). Although STA does not admit the dynamic intersection flows required to accurately model TBR, DTA does. Chapter 5 develops a CR model for TBR control in DTA, and Chapter 6 combines the CR model with the DTA four-step model to study the impacts of AVs on road conditions with greater accuracy.

5 RESERVATION-BASED INTERSECTION CONTROL IN DYNAMIC TRAFFIC ASSIGNMENT

5.1 Introduction

AVs have the potential to improve the road network in several ways, such as by increasing intersection capacity through the tile-based reservation (TBR) control policy proposed by Dresner and Stone (2004). TBR divides the intersection into tiles in space-time to monitor conflicts. Vehicles wishing to cross the intersection request to reserve tiles to ensure safe passage. Their request is accepted only if their path does not conflict with other vehicles, illustrated in Figure 1. The net result is that vehicles making conflicting movements (such as cross traffic) can simultaneously use the intersection through proper timing. Fajardo et al. (2011) demonstrated that TBR reduces delay beyond optimized traffic signals for a variety of demand scenarios.

Although TBR has been implemented in several custom micro-simulators, modeling this control over large city networks has yet to be accomplished due to the computational requirements. This is expected because micro-simulation is less appropriate for modeling city networks. However, this motivates the need for TBR integration into more aggregate flow models such as dynamic traffic assignment (DTA). A DTA model of TBR allows analyzing traffic flow under UE behavior. Although previous network-wide models of autonomous vehicles, such as Carlino et al. (2012), assumed routing to avoid congestion, predictions may differ when UE routing is considered. For instance, the greater capacity afforded by TBR-controlled intersections may also result in an increase in demand.

UE behavior becomes more important when considering prioritization strategies besides first-come-first-serve (FCFS) in TBR. Studies by Schepperle and Böhm (2007) and Carlino et al. (2013) proposed intersection auction schemes that reduce average intersection delay under heuristic routing behavior. Since intersections (both arterial crossings and highway merges/diverges) are often bottlenecks, this may place a price on the source of the congestion. However, the mechanisms leading to improvements are not fully understood; Carlino et al. (2013) used heuristic system bids to boost delay reductions, but how to choose optimal system bids is not clear. Moreover, the benefits may change due to vehicle routing behaviors. For instance, low-bidding vehicles may route to avoid auctions dominated by high-bidding vehicles. The primary obstruction to a more rigorous analysis of TBR is its micro-simulation definition, which has thus far prevented it from being studied in DTA. Improving computational feasibility and compatibility with DTA is the goal of this paper.

The contributions of this chapter are to develop a conflict region (CR) intersection model of TBR, compatible with general simulation-based DTA (SBDTA) models for solving for UE. The CR algorithm reduces the computational complexity of TBR but retains its properties of allowing simultaneous use of the intersection by potentially conflicting vehicles. The proposed model is also compatible with arbitrary vehicle prioritization schemes, including FCFS and auctions. We compare the CR model with results from micro-simulations of the TRB policy and analyze capacity on a single intersection case study. Finally, we implement the model in SBDTA to analyze the effect of auctions on traffic flow. Under UE behavior, much of the benefits of auctions appear to result from its randomizing effect. We compare results with a pure random policy and observe similar reductions in average travel time.

The remainder of this chapter is organized as follows. The CR model is proposed in Section 5.2. Section 5.3 compares the CR model with micro-simulation results from Fajardo et al. (2011) on a single intersection and demonstrates convergence of DTA on a city network. Conclusions are presented in Section 5.4.

5.2 Conflict region model

To motivate the reservation control model in DTA presented in Section 5.2.2, we first describe the requirements we seek to achieve in Section 5.2.1. As with TBR, the proposed model requires some knowledge about vehicle path through the intersection, which may be dependent on intersection geometry. We develop a method to automate finding these paths in Section 5.2.4.

5.2.1 Model requirements

To reduce the computational requirements of TBR sufficient for many simulations on city-size networks, we propose a simplified model to meet the following requirements:

- 1. The reservation policy model should be compatible with SBDTA in general, not restricted to a specific flow model. To accomplish this, the proposed algorithm builds on characteristics of general intersection models studied by Tampère et al. (2011).
- 2. The model should admit arbitrary prioritization schemes, such as FCFS and auctions. This is necessary to compare the effects of arbitrary prioritization strategies such as emergency vehicle-aware policies (Dresner and Stone, 2006) or auctions with system bids (Carlino et al., 2013).
- 3. The model should retain the simultaneous-use behavior of TBR, even by vehicles with potentially conflicting paths, to model the benefits of AV intersections. Without this, the model may not accurately predict vehicle behaviors and capacities of reservation policy intersections.
- 4. The model should be independent of specific intersection characteristics. Due to the number of intersections in city networks, tuning the model per intersection would be a time-consuming process as noted by Tampère et al. (2011). TBR requires tracing the path of a vehicle through a grid of tiles, which is dependent on intersection geometry. The proposed model reduces this to tracing the path through larger *conflict regions*. Section 3.3 presents an algorithm to divide intersections into conflict regions based on link angles.

In the development of this model, we make the following assumptions:

- 1. Flow is discretized to model vehicle-specific prioritization such as auctions. Applying such prioritizations to continuous flow requires additional study.
- 2. Vehicles are identical in terms of tiles occupied during turning movements. Many aggregate DTA models assume a characteristic, identical passenger vehicle, and we do the same here.
- 3. In the absence of other demand, flow between any incoming link to any outgoing link is restricted only by capacity of the two links. This is necessary to be as independent as possible from specific intersection geometry, as suggested by Tampère et al. (2011).

5.2.2 Intersection flow algorithm

The CR solution method is formalized in Figure 5.1 and described here in more detail. Consider an intersection with outgoing links Γ and incoming links Γ^{-1} . Divide the intersection into a set of non-overlapping conflict regions \Re . These conflict regions are intended to be much larger than tiles used in TBR, and are discussed in more detail in Section 5.3.4. Denote by \Re_{ij} the subset of \Re through which vehicles turning from $i \in \Gamma^{-1}$ to $j \in \Gamma$ will pass. (Note that in this chapter, i and j are referring to source and destination links rather than nodes). Let $q_{ij}(t)$ be the number of vehicles that have moved from i to j and $q_r(t)$ be the equivalent flow that has entered conflict region r in timestep t. (Note that t refers to a timestep rather than a larger assignment interval in this section). Let Q_i be the capacity of link i and $Q_{ij} = \max\{Q_i, Q_j\}$ be the capacity of the turning movement from i to j. Every tile has some capacity

$$Q_r = \max_{\left\{(i,j)|r\in\Re_{ij}\right\}} Q_{ij} \tag{5.1}$$

to allow flow of min $\{Q_i, Q_j\}$ for any (i, j) such that $r \in \Re_i j$ if no other demand is present. This definition of conflict region capacity, however, may overestimate vehicle movement if two turning movements that share a conflict region have different capacities. More specifically, consider the case where turning movements (1, 2) and (3,4) with capacities Q_{12} and Q_{34} share conflict point r. (The reduced capacities could be due to lower speeds or fewer lanes). Flow of Q_{12} from 1 to 2 should consume all supply of r, but valuing each vehicle as 1 flow through r leaves $Q_{34} - Q_{12}$ capacity unused capacity that might incorrectly be applied to flow from 3 to 4. Instead, each vehicle should consume $\frac{Q_r}{Q_{ij}}$ of the capacity of r.

Let ℓ_i be the number of lanes and $S_i(t)$ be the sending flow of link *i* at time t, i.e. the set of vehicles that could leave *i* at t if no other constraints were present. Each vehicle *v* has some priority defined by the arbitrary function f(v, i). The link is a parameter because vehicle priority could be different at different intersections. Let $R_j(t)$ be the receiving flow of link *j*, i.e. the number of vehicles that could enter *j* at *t* if incoming flow was infinite. Sending and receiving flows are general characteristics of dynamic flow models.

The algorithm works as follows: sort $S_i(t)$ by the time the vehicle entered link i. At time t, the first min $\{\ell_i, | S_i(t)\}$ vehicles from each $i \in \Gamma^{-1}$ are at the front of the queue and ready to enter the intersection. Let the set V_i comprise these vehicles for i. This preserves the first-in-first-out (FIFO) property: vehicles that arrived first reach the end of the link first. Note that these vehicles are not guaranteed to exit the link first because entering the intersection is dependent on the prioritization function. This is not a limiting assumption as it is potentially true for intersection controls in general; under traffic signals, left-turning vehicles may have to wait while later-arriving through traffic proceeds through the intersection.

We do not make a distinction for turning lanes because determining permitted turning movements for each lane could require intersection-specific information. As Tampère et al. (2011) note, such specific information could be difficult to acquire for each intersection in a city network. Furthermore, turning lane configurations currently used may not be used for autonomous vehicles.

Select the highest priority vehicle $v = \arg \max_{v' \in \bigcup_{i \in \Gamma^{-1}}} f(v')$ that can move, i.e. where capacity in all $r \in \Re_{ij}$ and receiving flow of j is sufficient considering vehicles that have already moved. This is the equivalent to reservations: each vehicle at the front of the queue for their link requests to enter the intersection. The highest priority request that is compatible with vehicles that have already entered is accepted.

1. Set $V = \emptyset$ 2. For all $i\in \Gamma^{-1}$ Sort $S_i(t)$ by arrival time at i3. Remove first ℓ_i vehicles in $S_i(t)$ and add them to V4. 5. End For 6. Sort V by f(v)7. For $\nu \in V$ traveling from i to jIf canMove(*i*, *j*) 8. $q_{ij}(t) \coloneqq q_{ij}(t) + 1$ 9. For $\mathcal{T} \in \mathcal{R}_{ij}$ 10. $y_r(t) \coloneqq y_r(t) + \frac{Q_{ij}}{Q_r}$ 11. 12.End For Remove first vehicle in $S_i(t)$ and add it to V13. Go to line 6 14. 15. End If 16. End For 17. function can Move($i \in \Gamma^{-1}, j \in \Gamma$) If $R_j - \sum_{i' \in \Gamma^{-1}} q_{i'j} < 1$ 18.Return False 19. 20.End If For all $\mathcal{N} \in \mathcal{R}_{ij}$ 21.If $Q_r - y_r < \frac{Q_{ij}}{Q_r}$ 22.23.Return False 24.End If End For 25.25.Return True

Figure 5.1: Simplified model of tile-based reservations for DTA

Let (i', j') be the incoming and outgoing link of v. Move v from i' to j'. This is the equivalent to blocking out tiles. Accepting the reservation of v reduces the remaining capacity of conflict regions in \Re_{ij} and remaining receiving flow of j. If $S_i(t)$ has remaining vehicles, add the earliest arrival time vehicle from $S_i(t)$ to V_i . Repeat selection of a vehicle until no vehicles can move.

5.2.3 Invariance principle

A major concern of Tampère et al.'s (2011) work on general intersection models was satisfaction of the invariance principle. When flow is less than sending flow, the demand at some infinitesimal point in time transitions to link capacity. If distribution of supply depends on demand, the flow allotted to a demand of link capacity may be different and therefore contradictory. An analogous situation may occur for supply.

The invariance principle for supply is satisfied because the solution distributes the supply (Tampère et al., 2011). However, the prioritization schemes by necessity consider demand in their allocation of supply, warranting a closer look at the invariance principle for demand. Due to lane blocking behavior, supply is distributed through vehicle prioritization on the vehicles at the front of the queue. If flow is constrained by supply, a change in demand on i from $|S_i(t)|$ to Q_i would not change the allocated supply because the priority of vehicles at the front of the queue on i would not change, and thus any demand behind those vehicles would be blocked from moving. Therefore the invariance principle of demand is also satisfied.

5.2.4 Division of intersection into conflict regions

A proper division of the intersection into conflict regions is vital to the proposed algorithm. Division into a grid of small tiles is more computationally demanding, and also requires more precise predictions of vehicle paths to determine which conflict regions are occupied. Tampère et al. (2011) in particular noted the necessity of intersection models to be as independent as possible of specific intersection geometry due to the potentially high number of intersections in city networks. Division into tiles of high granularity, for example one tile at the intersection of every two lanes, requires lane-specific vehicle paths. At the other extreme, no division at all (i.e. the entire intersection is one conflict region) may not properly capture vehicle interactions between specific turning movements. Capacity may be incorrectly borrowed from other areas of the intersection.

We propose a *radial division* into conflict regions at incoming and outgoing links, as shown in Figures 5.2 and 5.3. This division does not require lane-specific turning movements but limits supply of specific areas of the intersection. This division can also be determined geometrically when link angles are known by the method below. Link angles can be determined through node coordinates, which are readily available from internet-based geographic information systems.

The radial division method divides a circle into conflict regions through radii along incoming and outgoing link angles. Therefore any angle θ can be mapped to a conflict region; let $\mathbf{r}(\theta)$ be this mapping. Let θ_i be the angle of directed link *i*. The path from $i \in \Gamma^{-1}$ to $j \in \Gamma$ is assumed to be composed of two lines. Starting and ending coordinates of are shifted to the right by ϵ (for countries in which vehicles travel on their right, or $-\epsilon$ for vehicles traveling on their left), so that the paths do not follow conflict region boundaries. This results in starting coordinate s_i and ending coordinate s_j defined by

$$\boldsymbol{s}_{i} = \left(\cos\left(\theta_{i} + \pi\right), \sin\left(\theta_{i} + \pi\right)\right) + \epsilon \left(\cos\left(\theta_{i} - \frac{\pi}{2}\right), \sin\left(\theta_{i} - \frac{\pi}{2}\right)\right)$$
(5.2)

$$\boldsymbol{s}_{i} = \left(\cos\left(\theta_{i}\right), \sin\left(\theta_{i}\right)\right) + \epsilon \left(\cos\left(\theta_{i} - \frac{\pi}{2}\right), \sin\left(\theta_{i} - \frac{\pi}{2}\right)\right)$$
(5.3)

where π in this context is the ratio of a circle's circumference to its diameter, not a path.

Paths are defined by the intersection of the lines $\boldsymbol{l}_i(\zeta_i) = \boldsymbol{s}_i + \zeta_i(\cos(\theta_i), \sin(\theta_i))$ and $\boldsymbol{l}_i(\zeta_j) = \boldsymbol{s}_j + \zeta_j(\cos(\theta_j), \sin(\theta_j)).$

All conflict regions crossed by the turning movement path (determined through angles to the center of the circle) are added to \Re_{ij} . Choose ζ_i^* and ζ_j^* such that



Figure 5.2: Illustration of radial division on a three approach intersection The inner circle is divided by radii to the incoming and outgoing links.

$$\boldsymbol{l}_{i}\left(\zeta_{i}^{*}\right) = \boldsymbol{l}_{j}\left(\zeta_{j}^{*}\right). \text{ Then}$$
$$\Re_{ij} = \left\{\boldsymbol{r}\left(\tan^{-1}\left(\frac{s_{2}}{s_{1}}\right)\right) \mid (s_{1}, s_{2}) \in \left\{\boldsymbol{l}_{i}\left(\zeta\right) \mid 0 \leq \zeta \leq \zeta_{i}^{*}\right\} \cup \left\{\boldsymbol{l}_{j}\left(\zeta\right) \mid 0 \leq \zeta \leq \zeta_{j}^{*}\right\}\right\}$$
(5.4)

Although this path may not model the curves traced by real vehicles, such curves are unnecessary for this division because conflict regions are not lane-specific. Figure 5.2 demonstrates this method applied to a typical three approach intersection.

5.3 Numerical experiments

First, results on the single intersection scenario studied by Fajardo et al. (2011) were compared to those obtained using microsimulation. Then, the CR model was implemented on a city network to study convergence properties and computation time.

5.3.1 Single intersection case study

To analyze predictions of the CR model, the four approach, three lane intersection studied by Fajardo et al. (2011) was encoded. The link transmission model (Yperman, 2005) with a timestep of 10 seconds was used for flow propagation on links. The intersection was divided into four conflict regions, each the intersection of two directed links, as illustrated in Figure 5.2. Traffic passes through one, two, or three of these regions, depending on whether it is making a right turn, going through the intersection, or making a left turn, respectively. Since capacities were not specified by Fajardo et al. (2011), conservative estimates of 1200 vehicles per hour per lane were chosen. This results in each conflict region having a capacity of 3600 vehicles per hour. However, that is shared among all traffic passing through the region, including turning traffic.

The maximum demand cases were tested. Fajardo et al. (2011) reported average delay of 0.67 seconds per vehicle using their smallest buffer settings for demand of 1000 through vehicles, 200 right turning vehicles, and 100 left turning vehicles for each approach. The CR model predicted a similar average delay of 0 seconds (all vehicles that reached the end of the intersection moved through in the next timestep). Considering the relatively low total demand of 1300 vehicles per hour over 3 lanes, this is not surprising. As each conflict region in the case study is shared by two through movements, one right-turn movement, and three left-turn movements, the demand on each conflict region is 2400 vehicles per hour much less than the 3600 vehicle per hour capacity predicted. The small average delay of 0.67 seconds reported by Fajardo et al. (2011) could be due to small waiting times for tiles to clear. However, as the delay was much less than the 10 second timestep, it was not observed in the more aggregate CR model. The smallest buffer settings are most appropriate for comparison with the CR model because additional spacing requirements between vehicles was not assumed. Nevertheless, at all studied buffer settings the average delay was less than one timestep.

Similarly, Fajardo et al.'s (2011) left turn experiment, incorporating volumes of 1000 vehicles turning from approach 1 to 4, 1000 vehicles traveling through from



Figure 5.3: Single intersection case study

The 4 conflict regions are shaded, and turning movements from 2 are drawn to indicate which conflict regions they pass through. (Turning movements from other incoming links are symmetric). approach 3 to 1 (as shown in Figure 2), and 500 vehicles on all other through movements and 100 vehicles on all other turning movements, resulted in observed average delay of 0.69 seconds per vehicle using the smallest buffer settings. The maximum demand on any conflict region occurs in region D on Figure 2, which has a total demand of 2800 vehicles per hour still less than the 3600 vehicle per hour capacity. As a result, 0 delay is predicted for this scenario as well, which is similar to 0.69 seconds.

Unfortunately, intersection delay or capacity statistics for larger demands were not found in the literature. These would have been useful for validation purposes. Nevertheless, the CR model is built on capacity-restricted tiles, with capacity determined by incoming and outgoing links, and is therefore a reasonable approximation of TBR with reduced computational requirements.

5.3.2 City network

The CR model was implemented in a link transmission model (LTM) SBDTA (Yperman et al., 2005) with a 10 second timestep. Vehicles were discretized because of the requirements of the prioritization function in the intersection model. To reduce the computational requirements of path generation, demand was divided into assignment intervals of 15 minutes. To measure convergence, the gap function from Levin et al. (2014b) was used. Let t_v be the travel time of vehicle v and t_{rst}^* be the travel time of the shortest path from r to s departing within the assignment interval t. The cost gap as a percent of the total travel time is then

$$G = \frac{\sum\limits_{(r,s,t)^2 \times \mathcal{T}} \sum\limits_{v \in d_{rst}} (t_v - t_{rst}^*)}{\sum\limits_{(r,s,t)^2 \times \mathcal{T}} \sum\limits_{v \in d_{rst}} t_v} (5.5)$$

where Z is the set of zones, \mathcal{T} is the set of assignment intervals, and d_{rst} is the set of demand from r to s departing within $t \in \mathcal{T}$.

The method of successive averages (MSA) algorithm was used for convergence. On the nth iteration, $\frac{1}{n}$ vehicles were randomly chosen and moved to their shortest path. Using improved algorithms or heuristics (see Levin et al., 2014b) could further reduce the computation time. Since the purpose of this section is to demonstrate the computational tractability of SBDTA with the CR model, basic MSA was used.

Figure 5.4 shows the cost gap per iteration from running MSA on the downtown Austin network (Figure 3.1) with 2 hour AM peak demand, which has 171 zones, 546 intersections, 1247 links, and 62,836 trips. MSA exhibited a general trend of decreasing the cost gap despite occasional spikes. Running on an Intel Core i7-3770k at 4.2GHz, MSA required 922.5 seconds for 50 iterations, or an average of 18.5 seconds per iteration. This indicates that SBDTA with the CR model can be solved in a reasonable amount of time on city networks.

In contrast, currently the largest scale AV simulator is AORTA, which can simulate 15,000 vehicles in real time (Carlino et al., 2012) using a non-tile based reservation policy that reserves the entire intersection for vehicle movements. Running 50 iterations of MSA in AORTA on 15,000 vehicles (instead of 62,836) with a 3 hour simulation duration would require around 150 hours, which is much greater than the 0.26 hours recorded for the CR model. Even if CPU differences were accounted for, the CR model still reduces the computation time by at least two orders of magnitude. This is not unexpected, as AORTA (and other existing AV simulators) use micro-simulation, but these results demonstrate the importance of an efficient AV intersection model for DTA.

5.4 Conclusions

This chapter developed a SBDTA conflict region (CR) model of the tile-based reservation (TBR) intersection control policy for autonomous vehicles (AV) proposed by Dresner and Stone (2004, 2006a). The CR model reduces computation time yet retains the simultaneous-use characteristics of TBR. The model divides the intersection into conflict regions and restricts flow based on their capacity. Although the CR model requires some information about intersection geometry (as does TBR), we propose an algorithm to automate the division into conflict regions based on link angles. This allows large numbers of intersections in city networks to be modeled. By building on Tampère et al.'s (2011) work on general DTA intersection models,



Figure 5.4: Convergence of the method of successive averages in the downtown Austin network

the CR model is independent of the SBDTA flow model and satisfies characteristics such as first-in-first-out and the invariance principle. The computational tractability allows for the analysis of TBR controls under UE behavior, which previous studies on AV intersection controls have not considered. Combining the CR model with the integration of DTA and the four-step model allows for a planning model considering AV behavior, link capacity increases, and AV intersection controls in Chapter 6.

6 FOUR-STEP PLANNING WITH DYNAMIC TRAFFIC ASSIGNMENT AND AUTONOMOUS VEHICLES

6.1 Introduction

DTA offers important benefits over STA through its more accurate flow model. The lack of a hard capacity in STA and steady state model may underestimate the impact of additional trips on peak hour congestion. Specific for AVs, the greater detail in DTA admits AV behavior models such as TBR intersection control dynamics. Therefore this chapter modifies the four-step model in Chapter 4 to include the AV behaviors of link capacity increases and repositioning trips from Chapter 3 and the DTA model of TBR control from Chapter 5. The model is used for a comparison between zero and full AV ownership to study the effect of AVs on mode choice and network conditions under dynamic flow propagation and intersection controls.

6.1.1 Assumptions

In this DTA four-step model of AV behavior, we make the following assumptions:

1. All or nothing AVs: If both human-driven vehicles and AVs were considered, the proportion of AVs and correspondingly link capacity would vary with space and time. Implementing these varying capacities in DTA requires further study. Additionally, working with proportions of AVs requires a DTA intersection model for sharing intersections between AVs and human driven vehicles. Therefore, in this model we assume either all vehicles are AVs, or none are AVs.

- 2. The capacity of links, when travelers use AVs, is assumed to increase as described by Section 3.2. In the absence of literature on AV road capacity, Greenshields' (1935) model is used to estimate the scaling factor applied to the original network capacities.
- 3. When all vehicles are AVs, we assume that TBR controls are used to improve intersection capacity. The DTA model of TBR developed in Chapter 5 is used.
- 4. Repositioning trips: As in Chapter 3, AV return trips to the origin are permitted to avoid parking fees. Instead of parking costs, travelers who choose this mode incur additional fuel costs from the additional trip.
- 5. As in Chapter 3, we assume that AVs choose routes to minimize only their own travel cost. Although system coordination may reduce travel times on average, it may require some travelers to experience greater travel times. Therefore we assume that travelers do not accept system coordination and instead use UE behavior.

6.1.2 Contributions

This chapter presents a DTA four-step model incorporating AV roadway and traveler behaviors. DTA provides greater accuracy in flow propagation and admits the TBR intersection model for AVs. A case study compares the predicted trip, mode, and route choices with and without AVs on the downtown Austin city network. Although results predict higher link congestion overall than the static model in Chapter 3, the capacity improvements from AVs increase the average link speed despite significant increases in total numbers of personal vehicle trips. This optimistic finding suggests that AVs may improve the network despite increasing demand.

The remainder of this chapter is organized as follows: Section 6.2 discusses the changes to the DTA four-step model from Chapter 4. Section 6.3 presents numerical results, and Section 6.4 discusses conclusions.

6.2 Model formulation

The model formulation is based on the above work, but includes several new components. First, the cost function specific to this DTA four-step model of AV behavior is defined. Second, the solution method for the feedback model is described.

6.2.1 Generalized cost function

Although eco-routing has previously been studied in micro-simulations (Ahn and Rakha, 2008; Rakha et al., 2010) a UE approach in DTA has yet to be published in the literature. The more detailed energy consumption models developed in microsimulations and usable in DTA may have arbitrary properties preventing convergence (for instance, energy consumption may be lower at reduced speeds). Therefore, although trip and mode choice consider generalized costs based on travel time, fuel consumption, and desired arrival time, traffic assignment is based on travel times only. As discussed in Chapter 4, minimizing travel time is congruent to minimizing a generalized cost incorporating arrival time penalties.

The generalized cost function for trip and mode choice adds fuel consumption and link tolls to the arrival time penalty function of equation (4.1). Fuel consumption is calculated by Gardner et al. (2012)s regression equation, although the model does not exclude more detailed energy consumption calculations. The cost for the parking and transit modes is thus

$$C_{rst}^{PK} = \alpha t_{\pi_{rst}^* t} + \beta \left(0, T_{rs}^{pref} - \left(t_{\pi_{rst}^* t} + t \right) \right) \right)^+ + \gamma \left(t_{\pi_{rst}^* t} + t - T_{rs}^{pref} \right)^+ + F_{\pi_{rst}^* t} + t_{\pi_{rst}^* t} + \zeta_s^{PK}$$
(6.1)

$$C_{rst}^{\mathrm{TR}} = \alpha t_{\pi_{rst}^* t} + \beta \left(T_{rs}^{\mathrm{pref}} - \left(t_{\pi_{rst}^* t} + t \right) \right)^+ + \gamma \left(t_{\pi_{rst}^* t} + t - T_{rs}^{\mathrm{pref}} \right)^+ + \varsigma_s^{\mathrm{TR}}$$

$$(6.2)$$

where π_{rst}^* is the minimum cost path from r to s departing at t; $t_{\pi t}$ is the travel time, $F_{\pi t}$ the total fuel consumption, and $\tau_{\pi t}$ the sum of the link tolls for path π departing at t; and $(\cdot)^+ = \{0, \cdot\}$. Let t' denote the departure time of repositioning trips, i.e. $t'(t) = t + t_{\pi_{res}^{*}t}$. Then the cost for AV repositioning is

$$C_{rst}^{PK} = \alpha t_{\pi_{rst}^* t} + \beta \left(T_{rs}^{pref} - \left(t_{\pi_{rst}^* t} + t \right) \right)^+ + \gamma \left(t_{\pi_{rst}^* t} + t - T_{rs}^{pref} \right)^+ + F_{\pi_{rst}^* t} + t_{\pi_{rst}^*} + F_{\pi_{srt}^*(t)} t'(t) + t_{\pi_{srt}^* t'(t)}$$
(6.3)

These generalized costs are used in trip distribution and mode choice.

In reality, the departure times of repositioning trips should be linked to the arrival time of the travelers trip. However, the number of repositioning trips is determined in mode choice. Therefore, in line with the model in Section 3, the departure time of repositioning trips is set in the mode choice step to be the arrival time of the travelers trip. Changes in trip, mode, and route choice may result in the departure times of repositioning trips not matching the arrival time of the travelers trip. As the model converges, though, the changes between iterations in the trip table and travel times become small, and the departure times of repositioning trips then align with the arrival times of the corresponding travelers trips.

6.2.2 Solution method

The modified four-step model is solved as follows. Trip distribution, described by equations (4.2) through (4.9), is combined with the nested logit mode choice in equations (3.20) through (3.23) with an iterative MSA feedback as in equations (3.27) and (3.28). Traffic assignment used the MSA-TA heuristic, which was used in Chapter 4 with the four-step model and shown to converge on the downtown Austin network for DTA with the CR model in Chapter 5. As suggested by Boyce et al. (1994), the root mean squared error described by equation (4.10) was used to measure convergence of the four-step model.

6.3 Numerical results

This section presents results from a case study on the downtown Austin network with 2 hour AM peak demand, shown in Figure 3.1. As before, all trips are home-based work trips, and commercial travel or other types of personal travel may react differently. Three scenarios are compared: first, a scenario in which AVs are not allowed. Travelers only have the mode options of parking and transit, and intersections use traffic signals. The second scenario is full AV ownership; all travelers are assumed to drive AVs regardless of their mode choice. For the AV scenario, link capacity is scaled as defined by equations (3.5) and (3.6), but traffic signals are in use. The third scenario is the same as the second except that the CR model is used for all intersections. Travelers are predicted to choose between parking, repositioning, and transit through a nested logit model. Destination arrival times are based on a normal distribution as in Section 4.4.5.

First, Section 6.3.1 demonstrates the convergence and computation time of this four-step model. Section 6.3.2 discusses the impact on total trips and mode choice, and Section 6.3.3 shows the effects on traffic.

6.3.1 Convergence

Figure 6.1 shows that the feedback algorithm results in an overall decreasing trend in $RMSE^{d}$ even with AV repositioning trips and network capacity increases. This indicates that the model converges to a stable solution in terms of person trips and departure times. Figure 6.2 shows the computation time, running on an Intel Core i7-3770k at 4.2GHz. 15 iterations of the four-step feedback (including solving DTA as a sub-problem each iteration) required around 4 hours, which is an acceptable time for a city network. Most of the computation time is due to DTA, so use of faster DTA algorithms should improve computation time.

6.3.2 Effect on mode choice

Figure 6.3 compares the mode-specific trips for all scenarios. When AVs were in use, transit demand decreased by around 70%. The number of travelers parking their vehicle also decreased, with around 40,000 trips choosing the repositioning mode. These results are similar to those in Chapter 3; when AVs are available, travelers will decrease their use of transit and increase their use of AV repositioning trips. The net result is a significant increase in total personal vehicle trips. Table 6.1 shows that



Figure 6.1: Convergence of four-step model



Figure 6.2: Computation time of four-step model



Figure 6.3: Mode-specific trips

the total number of personal vehicle trips almost doubles when AV repositioning and TBR intersection controls are used.

On average, AV repositioning trips required \$0.87 in fuel costs and therefore were \$4.13 cheaper than parking in these scenarios. With average equivalent costs of \$6.10 for parking, a reduction of \$4.13 is a massive incentive even without considering the benefits of sharing the vehicle with other household members. Of course, these differences largely depend on the parking fee and network topology. The downtown Austin subnetwork has relatively short trips, and expanding the area of the network might include trips for which the parking fee is a smaller proportion of the monetary cost of the travel time. Also, parking may be a cheaper option for travelers who receive free parking from their employers. On the other hand, cities with limited parking and higher parking costs may experience a greater shift to repositioning trips.

Regardless, cities are likely to experience a significant decrease in parking demand. For this downtown Austin case study parking decreases by 31,571 trips when TBR and repositioning trips are included. That creates several options for city planners. With TBR, average link speeds increase even with repositioning trips,

	Total vehicle	Average link
	\mathbf{trips}	speed
Without AV repositioning	50,774	25.03
AV repositioning and traffic	94,050	24.51
signals		
AV repositioning and TBR	100,369	28.85
$\operatorname{control}$		

 Table 6.1: Effect of autonomous vehicles on total vehicle trips and average link

 speed

but encouraging parking might improve congestion even further. City planners may reduce fees or even subsidize parking to discourage repositioning trips. However, with an average fuel cost of \$0.87 for repositioning trips, parking would have to be rather cheap to be a favorable alternative. Another option is to reduce the number of parking spots and repurpose the space for other uses. For instance, street parking might be converted into another lane to increase capacity. Unused parking garages could be replaced with office space.

Overall, the total transit ridership is less than predicted by Chapter 3. This is due to several factors: first, in Chapter 3 most of the transit ridership is due to low VOT travelers, which make up a significant proportion of the population. Here, all travelers have the same VOT, so the proportion of AV ridership is less. This suggests that a multiclass DTA model for this scenario should be developed to study the effect on predictions. Also, greater congestion due to more realistic flow propagation in DTA results in relatively lower utility of transit with respect to driving. Finally, transit has fixed departure times in DTA which may not correspond with travelers preferred arrival times. (In STA those departure times are not modeled).

6.3.3 Effect on traffic

Despite the grim predictions for total trips, the net effect on traffic was positive when the TBR policy was used. Unlike the STA model in Chapter 3, which predicts modest increases in congestion as AV ownership increases, including DTA flow propagation and TBR intersection dynamics predicts an increase in average link speed, shown in Table 6.1. Average link speeds in Chapter 3 differ from those reported here because of the differences between static and dynamic flow models.

This indicates that the intersection capacity improvements of AVs made a significant contribution to the reduction in congestion. Furthermore, a map of the network in Figure 6.4 with speed changes shown on each link, indicates that the congestion benefits are present on most links. For arterial links, congestion propagates mostly from intersections, and therefore greater intersection capacity should relieve congestion. However, many highway links, which use merge/diverge intersections, also experience reductions in congestion. A significant portion of TBRs demonstrated improvements over signals come from simultaneous use by conflicting turning movements. Merge/diverge intersections do not have the potential for collision in the idealized DTA simulation, so flow is not limited by safety considerations as it is with signals. Therefore the improvements in congestion from TBR over signals on highway links indicates that greater capacity of arterial links alleviates some congestion propagation onto highway links.

In terms of policy implications, these results suggest that human usable (Dresner and Stone, 2006; 2007) TBR intersection controls should be implemented as soon as AVs comprise a sufficient proportion of the vehicles on the road. Also, allowing AV repositioning with traffic signals only slightly decreases link speed. Therefore the later departure times of repositioning trips and greater capacity from AVs mostly offsets the impact of the much greater demand.

6.3.4 Comparison of static and dynamic flow model predictions

This section performs a more detailed analysis of the different predictions from the STA and DTA models. The STA results from Chapter 3 are compared with the



Figure 6.4: Speed comparison between signals and TBR controls Use of TBR controls results in a lower speed for links in blue and a higher speed for links in red.

Links without a significant change are not emphasized.

DTA results from the model developed in Section 6.2. Although DTA is the more accurate flow model, the STA model admits multiple classes including human and autonomous vehicles operating at different VOTs whereas DTA is limited to either entirely human or autonomous vehicles. The comparisons in this section are made to demonstrate the potential differences in predictions, but the STA models value remains due to its ability to analyze a gradual AV availability scenario. Users of the STA models predictions, however, should be aware of the differences in network congestion between the two models.

First, the base scenario of entirely human-driven vehicles is compared in Figure 6.5. Link speeds are used to measure congestion because flow affects link travel times differently for STA and DTA. For DTA, average link speeds over the first two hours are considered. Due to the desired arrival time distribution, most vehicles will arrive within the first two hours of the simulation. For many links DTA predicts significantly lower speeds. DTA predicts greater speeds on a few links in the southwest portions of Mopac and northeast portions of I-35, and similar speeds to STA on some arterials. In the downtown region and on arterials this results from limited intersection capacity causing delays for vehicles on those links. On some highway segments, although STA predicts reduced speed as a function of flow, in DTA the link may be closer to free flow due to higher capacity.

Figures 6.6 and 6.7 compare speeds resulting from the introduction of AV repositioning trips and link capacity into STA and DTA, respectively. For DTA, traffic signals are used with and without AV behaviors, but intersection capacity is scaled with link capacity when AVs are included. It is immediately clear from Figure 6.6 that although STA predicts average reductions in link speed, only a subset of links are affected. The greatest impact occurs along Guadalupe, but overall most of the effect appears to be along three north-south routes. Because much of the peak demand in this network is for travel to the downtown area, the increase in personal vehicle trips to the downtown area and in repositioning trips returning to the origin increases the total demand on north-south routes. Since STA lacks a consideration of departure times, these trips increase flow and reduce the link speed on north-south routes. Even in the downtown grid, most of the congestion due to AVs is along the



Figure 6.5: Speed comparison between static and dynamic models with humandriven vehicles

DTA predicts a lower speed for links in blue and a higher speed for links in red. Links without a significant change are not emphasized. north-south running Guadalupe and Lavaca.

The link speed predictions of STA in Figure 6.6 should be contrasted with the predictions of DTA in Figure 6.7, which show much the opposite pattern. DTA predicts a similar number of additional north-south demand due to lower transit ridership and a switch to repositioning trips. However, because repositioning trips depart after the traveler reaches the destination, much of the additional north-south demand is for a later time period. Therefore greater congestion on north-south routes is not as pronounced as it is with STA.

On the other hand, a major inaccuracy with STA is the lack of congestion propagation, particularly in the downtown grid. While greater flow will reduce travel times for STA, the short links and high demand result in high density that limits both speed and the number of vehicles that can enter the link. As a result, many arterial links and links in the downtown region experience greater congestion as a result of AVs. However, DTA also predicts that many links will experience higher speeds from AVs. In contrast, few links in STA are improved because of the monotonicity of the STA travel time function with capacity increase. With DTA, though, variability in departure times and greater intersection capacity improve the congestion on many links. It is difficult to determine a clear pattern as to whether congestion on a specific link is likely to increase or decrease after the switch to AVs. Therefore, it largely depends on the combination of network topology and travel demand.

This comparison between network congestion predictions between STA and DTA shows great similarities in terms of total trips per mode. For long-term predictions of transit ridership and number of repositioning trips, STA may thus be sufficient. STA has several advantages, such as being easier to calibrate and requiring less computational resources. Also, the STA model is designed for multiple classes as well as shared human and AV roads, which makes it valuable for studying the effects of gradual AV ownership. On the other hand, network congestion predictions, particularly those that study specific roads, may be more accurate when using DTA. Besides the more realistic flow model, the impact of AV repositioning trips is fairly dependent on departure times, as many repositioning trips travel after desired work arrival times.



Figure 6.6: Speed comparison with and without AV behaviors using STA Repositioning trips predicts a lower speed for links in blue and a higher speed for links in red.

Links without a significant change are not emphasized.



Figure 6.7: Speed comparison with and without AV behaviors using DTA and traffic signals

Inclusion of repositioning trips result in lower speed predictions for links in blue and higher speed predictions for links in red.

Links without a significant change are not emphasized.
6.4 Conclusions

This chapter developed a four-step model incorporating DTA with departure time choice from Chapter 4, AV repositioning trips and link capacity improvements from Chapter 3, and the CR intersection model from Chapter 5. Although traffic assignment did not incorporate fuel consumption into the cost function, fuel costs were included in trip and mode choice predictions. The resulting model was used to analyze the effects of AVs on mode choice and network congestion. Mode choice predictions were similar to those in Chapter 3; transit ridership decreases and the total number of personal vehicle trips greatly increases due to the option of AV repositioning trips. However, traffic congestion predicted by DTA differed. Overall, total congestion was higher, but AV link and intersection capacities improved average link speeds. In Chapter 3, the increased demand was observed to be offset by increased capacity due to reduced following headways and the fact that repositioning trips are likely to use different links. In DTA, two additional factors are relevant to the reduced congestion: first, TBR increases intersection capacity, which is a major bottleneck in the downtown region; and second, repositioning trips, on average, depart later. This results in less of an increase in road demand at any given time. The increase in average link speeds offers a more optimistic view of AVs: despite the increases in demand, the capacity improvements may yet offer a benefit to traffic networks. However, because of the much greater demand, the greater capacity offered by AVs may not be a complete solution for traffic network congestion.

7 CONCLUSIONS

7.1 Summary of contributions

To predict the effects AVs have on trip, mode, and route choice, this thesis developed a DTA four-step model incorporating AV behaviors for a variety of Austin, Texas applications. First, AV capacity and repositioning trips to avoid parking fees were added to the STA four-step model. Next, DTA was integrated into the four-step model using Vickrey's (1969) arrival time penalty function to endogenously determine departure time distributions for each OD. A CR-based algorithm was developed to model the TBR intersection control proposed by Dresner and Stone (2004, 2005) for AVs in DTA. Finally, the various steps were combined into a single model.

7.1.1 Autonomous vehicles in static four-step planning

Two AV behaviors were incorporated into the STA multi-class four-step model. Because AVs allow repositioning trips (where the vehicle drives itself empty), a third mode of repositioning to the origin was included to avoid parking fees (at the cost of greater fuel consumption and roadway congestion), in addition to the modes of parking and transit. A nested logit model was used to predict traveler choices between modes. The second AV behavior included was reduced following distance leading to greater link capacity. Capacity was scaled as a function of the proportion of AVs on each link based on Greenshields' (1935) model. With multiple classes, the model can be used for scenarios in which only a segment of the population owns AVs.

A generalized cost function including link fuel consumption based on Gardner et al. (2013) was used for routing. Traffic assignment was formulated as a VI because although the cost function (including the scaling capacity) is monotone increasing with respect to flow for any class, with multiple classes the Jacobian is not positive semi-definite. A heuristic based on Frank-Wolfe was shown to converge on the downtown Austin city network.

In a case study on downtown Austin with 2 hour AM peak demand, travelers were separated into classes based on income, with corresponding VOTs, and the scenario of gradual AV ownership (as AVs become affordable to different segments of the population) was studied. Due to lack of data, all trips were assumed to be home-based work travel. After full AV ownership, personal vehicle trips increased greatly due to two factors: first, transit ridership decreased substantially. Second, the majority of travelers choosing to drive chose repositioning trips to avoid parking fees. Despite the high increase in trips, the increase in capacity offset much of the additional congestion. Reductions in average link speed were modest. Also, most of the increase in personal vehicle trips occurred when AVs became available to lowincome travelers, who made up most of the transit ridership. City planners may thus have some time after AVs become available to consumers to prepare for the increase in trips and reduction in transit ridership when AVs become affordable for all travelers.

7.1.2 Departure time choice in dynamic traffic assignment

To facilitate the study of AV behaviors in DTA, which allows more detailed predictions of AV roadway dynamics and TBR intersection control, DTA was integrated into the four-step planning model. A major question for DTA planning models is the distribution of departure times (Peeta and Ziliaskopoulos, 2001). To address this, a time index was added to trip distribution and mode choice, and Vickrey's (1969) arrival time penalty function was used to discourage travel at times that resulted in early or late arrivals at the destination. The desired arrival time could be specific to each OD to model different work start times. Because the four-step model is still widely used, this integration may be valuable for practitioners who wish to incorporate DTA without changing to a different planning model.

The endogenous departure time choice was compared against a OD-independent departure time profile, as used in previous studies on integrating DTA into the fourstep model, on the downtown Austin city network. Most departure times were chosen so travelers arrived at the destination near their desired arrival times. This resulted in an asymmetric assignment and greater congestion, which could impact level of service and environmental impact analyses. Neither STA nor DTA with an OD-independent departure time profile could capture these departure time predictions. Although a normally distributed arrival time preferences resulted in an overall bell curve shape for the departure time distribution, it still varied significantly for different ODs.

7.1.3 Autonomous vehicle intersections in dynamic traffic assignment

The TBR policy (Dresner and Stone, 2004, 2005) is a major intersection improvement for AVs that has received considerable attention in the literature. However, as it is based on a micro-simulation intersection model, studies have yet to incorporate UE behavior. This makes it difficult to evaluate its effects on city networks. As Braess (1968) demonstrated, increasing capacity may not necessarily reduce travel times due to selfish routing. To study TBR under UE behavior, a CR model of TBR was developed for DTA. It retains the simultaneous-use by conflicting turning movements characteristic yet greatly reduces the computation time, allowing DTA to be solve as a sub-problem to planning models.

Although the CR model was used in this thesis as an additional road capacity from AVs, in future work a DTA model incorporating AV intersection controls will allow a variety of studies. For instance, simulating AV intersections on networks will become much faster through DTA, and the effects of priority schemes other than FCFS may be studied under UE behavior.

7.1.4 Four-step planning with autonomous vehicles and dynamic traffic assignment

The models developed in Chapters 3, 4 and 5 were combined into a single planning model for more accurate predictions of the effects of AVs on travel demand and traffic congestion. The combined model was built on the integration of DTA into the four-step model with departure time choice. Intersection controls used the CR model simplification of the TBR policy proposed by Dresner and Stone (2004). Link capacity was scaled using a heuristic based on Greenshields' (1935) capacity model, and the AV repositioning mode gave travelers an option to drive while avoiding parking costs.

Results from the DTA four-step model with AV behaviors were more optimistic in some regards than those from the STA four-step model. Although overall traffic congestion was predicted to be worse, both with and without AVs, the DTA planning model predicted an overall decrease in average congestion when AVs were present despite almost double the number of total vehicle trips. This was due to several factors including the addition of intersection capacity improvements through the TBR policy and the later departure time of AV repositioning trips. This suggests that although AVs may not solve network congestion issues, they may improve congestion slightly. Also, for the most accurate predictions of traffic networks with AV behaviors, DTA rather than STA should be used in conjunction with planning models.

7.2 Future work

Due to the small amount of literature on AVs in traffic models, this thesis made a number of assumptions that should be validated or relaxed in future work. First, the link capacity increases were based on an assumption about reduced following distance resulting in higher density. Then, capacity was scaled according to Greenshields' (1935) model. Further study on AV following distances and how they affect capacity would improve the accuracy of the capacity model. For DTA, the effect of reduced headways on capacity is dynamic as the proportion of AVs changes with time. A multiclass dynamic flow model should be developed to more accurately capture the effects of increasing AV proportions on the traffic network. DTA models might also incorporate the increased stability and backwards wave speed observed in microsimulation (Schakel et al., 2010).

The CR model admits study of various prioritization strategies. The FCFS strategy may not be optimal in terms of capacity or queue length. Also, intersections are often a significant source of energy consumption and greenhouse gas emissions because deceleration-acceleration cycles are inefficient for conventional internal combustion engine vehicles. A significant issue is that any such strategy will affect driver route choice, assuming they act independently to minimize travel costs. The CR model could be useful in determining the effectiveness of new and existing prioritization strategies under UE routing.

AV owners had the behavior option of repositioning to the origin to avoid parking fees at the cost of additional fuel. In reality, repositioning utility is likely to be greater because it allows the vehicle to be shared with other household members. For instance, two workers from the same household with sufficiently different work start times could use the same vehicle for their home-to-work trips. An activitybased model considering household vehicle sharing might model these preferences with greater accuracy. At the minimum, studies on disutility and traveler preference for repositioning trips should be conducted to better calibrate the model.

In addition, AVs are likely to make IVTT less onerous for travelers because they may engage in other activities during travel, much like in public transit. Furthermore, riding in a personal vehicle may be more comfortable than riding in transit. Therefore, traveler preferences for driving rather than transit may be different for AV owners. However, these preferences are affected by transit options. Further study may suggest how to improve the attractiveness of transit to AV owners. A further consideration of repositioning trips is their impact on parking costs. The greatly reduced demand for parking may result in lower parking costs until a balanced is reached with the fuel cost of repositioning. Parking may be partly subsidized or owned by the government to reduce the demand on the network. Alternately, it may be more cost effective to convert space formerly used for parking into additional developments or road capacity.

References

- AHN, K., & RAKHA, H. (2008). The effects of route choice decisions on vehicle energy consumption and emissions. *Transportation Research Part D: Transport* and Environment, 13(3), 151-167.
- AZIZ, H. M., & UKKUSURI, S. V. (2012). Integration of environmental objectives in a system optimal dynamic traffic assignment model. *Computer Aided Civil* and Infrastructure Engineering, 27(7), 494-511.
- BANDEIRA, J., CARVALHO, D. O., KHATTAK, A. J., ROUPHAIL, N. M., & COELHO, M. C. (2012). A comparative empirical analysis of eco-friendly routes during peak and off-peak hours. In 91st Annual Meeting of Transportation Research Board.
- BAR-GERA, H., & BOYCE, D. (2003). Origin-based algorithms for combined travel forecasting models. Transportation Research Part B: Methodological, 37(5), 405-422.
- BARTH, M., BORIBOONSOMSIN, K., & VU, A. (2007, September). Environmentally-friendly navigation. In Intelligent Transportation Systems Conference, 2007. ITSC 2007. IEEE (pp. 684-689). IEEE.
- BELLEI, G., GENTILE, G., MESCHINI, L., & PAPOLA, N. (2006). A demand model with departure time choice for within-day dynamic traffic assignment. *European journal of operational research*, 175(3), 1557-1576.

- BENEDEK, C. M., & RILETT, L. R. (1998). Equitable traffic assignment with environmental cost functions. *Journal of transportation engineering*, 124(1), 16-22.
- BERA, S., & RAO, K. V. (2011). Estimation of origin-destination matrix from traffic counts: the state of the art.
- BERNSTEIN, D., FRIESZ, T. L., & TOBIN, R. L. (1993). A variational control formulation of the simultaneous route and departure-time choice equilibrium problem. In International Symposium on the Theory of Traffic Flow and Transportation, 12th, 1993, Berkeley, California, USA.
- BHAT, C. R., & KOPPELMAN, F. S. (1999). Activity-based modeling of travel demand. In *Handbook of transportation Science* (pp. 35-61). Springer US.
- BLIEMER, M. C., & VAN AMELSFORT, D. H. (2010). Rewarding instead of charging road users: a model case study investigating effects on traffic conditions.
- BOYCE, D. E., ZHANG, Y. F., & LUPA, M. R. (1994). Introducing" feedback" into four-step travel forecasting procedure versus equilibrium solution of combined model. *Transportation Research Record*, 65-65.
- BRAESS, P. D. D. D. (1968). ber ein Paradoxon aus der Verkehrsplanung. Unternehmensforschung, 12(1), 258-268.
- BURNS, L. D., JORDAN, W. C., & SCARBOROUGH, B. A. (2013). Transforming personal mobility. *The Earth Institute*.
- CAPLICE, C., & MAHMASSANI, H. S. (1992). Aspects of commuting behavior: preferred arrival time, use of information and switching propensity. Transportation Research Part A: Policy and Practice, 26(5), 409-418.
- CARLINO, D., DEPINET, M., KHANDELWAL, P., & STONE, P. (2012, September). Approximately orchestrated routing and transportation analyzer: Large-scale

traffic simulation for autonomous vehicles. In Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference(pp. 334-339). IEEE.

- CARLINO, D., BOYLES, S. D., & STONE, P. (2013, October). Auction-based autonomous intersection management. In *Proceedings of the 16th IEEE Intelligent Transportation Systems Conference (ITSC).*
- CHIU, Y. C., & BUSTILLOS, B. (2009). A gap function vehicle-based solution procedure for consistent and robust simulation-based dynamic traffic assignment. In *Transportation Research Board 88th Annual Meeting* (No. 09-3721).
- CHIU, Y. C., BOTTOM, J., MAHUT, M., PAZ, A., BALAKRISHNA, R., WALLER, T., & HICKS, J. (2011). Dynamic traffic assignment: A primer. Transportation Research E-Circular, (E-C153).
- DAGANZO, C. F. (1994). The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B: Methodological*, 28(4), 269-287.
- DAGANZO, C. F. (1995). The cell transmission model, part II: network traffic. Transportation Research Part B: Methodological, 29(2), 79-93.
- DE LA ESCALERA, A., ARMINGOL, J. M., & MATA, M. (2003). Traffic sign recognition and analysis for intelligent vehicles. *Image and vision computing*, 21(3), 247-258.
- DE PALMA, A., & LINDSEY, R. (2011). Traffic congestion pricing methodologies and technologies. Transportation Research Part C: Emerging Technologies, 19(6), 1377-1399.
- DIAL, R. B. (2006). A path-based user-equilibrium traffic assignment algorithm that obviates path storage and enumeration. *Transportation Research Part* B: Methodological, 40(10), 917-936.

- DIXON, M. P., & RILETT, L. R. (2002). RealTime OD Estimation Using Automatic Vehicle Identification and Traffic Count Data. ComputerAided Civil and Infrastructure Engineering, 17(1), 7-21.
- DRESNER, K., & STONE, P. (2004, July). Multiagent traffic management: A reservation-based intersection control mechanism. In Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 2 (pp. 530-537). IEEE Computer Society.
- DRESNER, K., & STONE, P. (2005, July). Multiagent traffic management: An improved intersection control mechanism. In Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems (pp. 471-477). ACM.
- DRESNER, K., & STONE, P. (2006, May). Human-usable and emergency vehicleaware control policies for autonomous intersection management. In Fourth International Workshop on Agents in Traffic and Transportation (ATT), Hakodate, Japan.
- DRESNER, K. M., & STONE, P. (2007, January). Sharing the Road: Autonomous Vehicles Meet Human Drivers. In *IJCAI* (Vol. 7, pp. 1263-1268).
- DUTHIE, J. C., NEZAMUDDIN, N., JURI, N. R., RAMBHA, T., MELSON, C., POOL, C. M., ... & KUMAR, R. (2013). Investigating Regional Dynamic Traffic Assignment Modeling for Improved Bottleneck Analysis: Final Report (No. FHWA/TX-13/0-6657-1).
- ERICSSON, E., LARSSON, H., & BRUNDELL-FREIJ, K. (2006). Optimizing route choice for lowest fuel consumptionPotential effects of a new driver support tool. Transportation Research Part C: Emerging Technologies, 14(6), 369-383.
- FAGNANT, D., & KOCKELMAN, K. (2013). Environmental Implications for Autonomous Shared Vehicles Using Agent-Based Model Simulation. Working paper, University of Texas at Austin.

- FAGNANT, D. J., & KOCKELMAN, K. M. (2014a). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transportation Research Part C: Emerging Technologies, 40, 1-13.
- FAGNANT, D. J., & KOCKELMAN, K. (2014b). Preparing a nation for autonomous vehicles: opportunities, barriers, and policy recommendations. *Transportation Research*, 20.
- FAGNANT, D. J., KOCKELMAN, K. M., & BANSAL, P. (2015a). Operations of a Shared Autonomous Vehicle Fleet for the Austin, Texas Market. 94th Annual Meeting of the Transportation Research Board, January 2015, Washington D.C.
- FAGNANT, D. J., & KOCKELMAN, K. M. (2015b). Dynamic Ride-Sharing and Optimal Fleet Sizing for a System of Shared Autonomous Vehicles. 94th Annual Meeting of the Transportation Research Board, January 2015, Washington D.C.
- FAJARDO, D., AU, T. C., WALLER, S. T., STONE, P., & YANG, D. (2011). Automated Intersection Control. Transportation Research Record: Journal of the Transportation Research Board, 2259(1), 223-232.
- FEDERAL HIGHWAY ADMINISTRATION (2009). National Household Travel Survey. U.S. Department of Transportation. Washington, D.C.
- FISHER, A. (2013). Inside Googles quest to popularize self-driving cars. Popular Science, September 18, 2013.
- FREY, H. C., ZHANG, K., & ROUPHAIL, N. M. (2008). Fuel use and emissions comparisons for alternative routes, time of day, road grade, and vehicles based on in-use measurements. *Environmental science & technology*, 42(7), 2483-2489.

- FRIESZ, T. L., BERNSTEIN, D., SMITH, T. E., TOBIN, R. L., & WIE, B. W. (1993). A variational inequality formulation of the dynamic network user equilibrium problem. *Operations Research*, 41(1), 179-191.
- FRIESZ, T. L., D. BERNSTEIN, Z. SUO, & R.L. TOBIN. (2001). Dynamic network user equilibrium with state-dependent time lags. *Networks and Spatial Economics*, 1(3-4), 319-347.
- FUEL PROPERTIES COMPARISON. Alternative Fuels Data Center. U.S. Department of Energy, Web, Accessed June 21, 2013. http://www.afdc.energy.gov/fuels/fuel comparison chart.pdf.
- GARDNER, L. M., DUELL, M., & WALLER, S. T. (2013). A framework for evaluating the role of electric vehicles in transportation network infrastructure under travel demand variability. *Transportation Research Part A: Policy and Practice*, 49, 76-90.
- GHALI, M. O., & SMITH, M. J. (1995). A model for the dynamic system optimum traffic assignment problem. Transportation Research Part B: Methodological, 29(3), 155-170.
- GONZALES, E.J., & C.F. DAGANZO. (2012). Morning commute with competing modes and distributed demand: User equilibrium, system optimum, and pricing. Transportation Research Part B: Methodological, 46(10), 1519-1534.
- GREENHOUSE GAS EMISSIONS: TRANSPORTATION SECTOR EMIS-SIONS. Environmental Protection Agency, n.d. Web. 26 Nov. 2013. http://www.epa.gov/climatechange/ghgemissions/sources/transportation.html¿.
- GREENSHIELDS, B. D., CHANNING, W., & MILLER, H. (1935). A study of traffic capacity. In *Highway research board proceedings* (Vol. 1935). National Research Council (USA), Highway Research Board.

- GUO, F., RAKHA, H., & PARK, S. (2010). Multistate model for travel time reliability. Transportation Research Record: Journal of the Transportation Research Board, 2188(1), 46-54.
- HAN, L., UKKUSURI, S., & DOAN, K. (2011). Complementarity formulations for the cell transmission model based dynamic user equilibrium with departure time choice, elastic demand and user heterogeneity. *Transportation Research Part B: Methodological*, 45(10), 1749-1767.
- KESTING, A., TREIBER, M., & HELBING, D. (2010). Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. *Philo*sophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 368(1928), 4585-4605.
- KOLAK, O. I., BIRBIL, S. I., FEYZIOGLU, O., NOYAN, N., & YALNDAG, S. (2013). Using emission functions in modeling environmentally sustainable traffic assignment policies. *Journal of Industrial and Management Optimiza*tion, 9(2), 341-363.
- LI, Y., ZILIASKOPOULOS, A. K., & WALLER, S. T. (1999). Linear programming formulations for system optimum dynamic traffic assignment with arrival time-based and departure time-based demands. *Transportation Research Record: Journal of the Transportation Research Board*, 1667(1), 52-59.
- LI, Q., ZHENG, N., & CHENG, H. (2004). Springrobot: A prototype autonomous vehicle and its algorithms for lane detection. *Intelligent Transportation Sys*tems, IEEE Transactions on, 5(4), 300-308.
- LIN, D. Y., ELURU, N., WALLER, S. T., & BHAT, C. R. (2008). Integration of activity-based modeling and dynamic traffic assignment. Transportation Research Record: Journal of the Transportation Research Board, 2076(1), 52-61.
- LIN, D. Y., VALSARAJ, V., & WALLER, S. T. (2011). A Dantzig Wolfe Decomposition Based Heuristic for Offline Capacity Calibration of Dynamic Traffic

Assignment. Computer Aided Civil and Infrastructure Engineering, 26(1), 1-15.

- LIU, Y., & NIE, Y. M. (2011). Morning commute problem considering route choice, user heterogeneity and alternative system optima. *Transportation Re*search Part B: Methodological, 45(4), 619-642.
- LEVIN, M. W., BOYLES, S. D., & NEZAMUDDIN (2014a). Warm-starting dynamic traffic assignment with static solutions. *Transportmetrica B: Transport Dynamics*, 1-15.
- LEVIN, M. W., POOL, M., OWENS, T., JURI, N. R., & WALLER, S. T. (2014b). Improving the Convergence of Simulation-based Dynamic Traffic Assignment Methodologies. *Networks and Spatial Economics*, 1-22.
- LO, H. K., & CHEN, A. (2000). Reformulating the traffic equilibrium problem via a smooth gap function. *Mathematical and computer modelling*, 31(2), 179-195.
- LÓPEZ, E., & MONZÓN, A. (2010). Integration of Sustainability Issues in Strategic Transportation Planning: A Multicriteria Model for the Assessment of Transport Infrastructure Plans. Computer aided Civil and Infrastructure Engineering, 25(6), 440-451.
- LU, C. C., MAHMASSANI, H. S., & ZHOU, X. (2009). Equivalent gap functionbased reformulation and solution algorithm for the dynamic user equilibrium problem. *Transportation Research Part B: Methodological*, 43(3), 345-364.
- MARSDEN, G., MCDONALD, M., & BRACKSTONE, M. (2001). Towards an understanding of adaptive cruise control. *Transportation Research Part C: Emerging Technologies*, 9(1), 33-51.
- MCNALLY, M. G. (2008). The four step model. *Center for Activity Systems* Analysis.

- MERCHANT, D. K., & NEMHAUSER, G. L. (1978). A model and an algorithm for the dynamic traffic assignment problems. *Transportation Science*, 12(3), 183-199.
- MINETT, C. F., SALOMONS, A. M., DAAMEN, W., VAN AREM, B., & KUIJPERS, S. (2011, June). Eco-routing: comparing the fuel consumption of different routes between an origin and destination using field test speed profiles and synthetic speed profiles. In *Integrated and Sustainable Transportation System* (FISTS), 2011 IEEE Forum (pp. 32-39). IEEE.
- NAGURNEY, A., RAMANUJAM, P., & DHANDA, K. K. (1998). A multimodal traffic network equilibrium model with emission pollution permits: compliance vs noncompliance. *Transportation Research Part D: Transport and Environment*, 3(5), 349-374.
- NAGURNEY, A. (2000). Congested urban transportation networks and emission paradoxes. Transportation Research Part D: Transport and Environment, 5(2), 145-151.
- NEWELL, G. F. (1987). The morning commute for nonidentical travelers. *Transportation Science*, 21(2), 74-88.
- OAKLEY, E. The Race to the Autonomous Car. *Berkeley Political Review*. UC Berkeley, n.d. Web. 07 Feb. 2014.
- OZGUNER, U., STILLER, C., & REDMILL, K. (2007). Systems for safety and autonomous behavior in cars: The DARPA Grand Challenge experience. *Proceedings of the IEEE*, 95(2), 397-412.
- PEETA, S., & MAHMASSANI, H. S. (1995). System optimal and user equilibrium time-dependent traffic assignment in congested networks. Annals of Operations Research, 60(1), 81-113.

- PEETA, S., & ZILIASKOPOULOS, A. K. (2001). Foundations of dynamic traffic assignment: The past, the present and the future. *Networks and Spatial Economics*, 1(3-4), 233-265.
- PENDYALA, R. & BHAT, C. (2014). Setting the Stage: Activity-Travel Behavior Impacts of Driverless Cars. Proceedings of the 93rd Annual Meeting of the Transportation Research Board.
- POLZIN, S., WALKER, J., MAHMASSANI, H., CHARLTON, B. (2014). Potential Activity-Travel and Land Use Impacts of Driverless Cars. *Proceedings of the* 93rd Annual Meeting of the Transportation Research Board.
- POOL, M. Enhancing the Practical Usability of Dynamic Traffic Assignment. MS Thesis University of Texas at Austin, 2012.
- RAKHA, H. A., AHN, K., & MORAN, K. (2012). INTEGRATION framework for modeling eco-routing strategies: Logic and preliminary results. *International Journal of Transportation Science and Technology*, 1(3), 259-274.
- RAMADURAI, G., & UKKUSURI, S. (2011). BDynamic: An Efficient Algorithm for Dynamic User Equilibrium Assignment in ActivityTravel Networks. Computer aided Civil and Infrastructure Engineering, 26(4), 254-269.
- RAN, B., & BOYCE, D. (1994). Dynamic urban transportation network models: theory and implications for intelligent vehicle-highway systems (No. 417).
- RILETT, L. R., & BENEDEK, C. M. (1994). Traffic assignment under environmental and equity objectives. *Transportation research record*, 92-92.
- SCHAKEL, W. J., VAN AREM, B., & NETTEN, B. D. (2010, September). Effects of cooperative adaptive cruise control on traffic flow stability. In Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference (pp. 759-764). IEEE.

- SCHEPPERLE, H., & BÖHM, K. (2007). Agent-based traffic control using auctions. In *Cooperative Information Agents XI* (pp. 119-133). Springer Berlin Heidelberg.
- SCHEPPERLE, H., & BÖHM, K. (2008, July). Auction-based traffic management: Towards effective concurrent utilization of road intersections. In E-Commerce Technology and the Fifth IEEE Conference on Enterprise Computing, E-Commerce and E-Services, 2008 10th IEEE Conference (pp. 105-112). IEEE.
- SHEFFI, Y. (1985). Urban transportation networks: equilibrium analysis with mathematical programming methods.
- SWEET, M. N., & CHEN, M. (2011). Does regional travel time unreliability influence mode choice? *Transportation*, 38(4), 625-642.
- SUGAWARA, S., & NIEMEIER, D. A. (2002). How much can vehicle emissions be reduced? Exploratory analysis of an upper boundary using an emissionsoptimized trip assignment. Transportation Research Record: Journal of the Transportation Research Board, 1815(1), 29-37.
- SZETO, W. Y., & LO, H. K. (2004). A cell-based simultaneous route and departure time choice model with elastic demand. *Transportation Research Part* B: Methodological, 38(7), 593-612.
- TAMPÈRE, C. M., CORTHOUT, R., CATTRYSSE, D., & IMMERS, L. H. (2011). A generic class of first order node models for dynamic macroscopic simulation of traffic flows. *Transportation Research Part B: Methodological*, 45(1), 289-309.
- TRANSPORTATION RESEARCH BOARD. (1965). Special Report 87: Highway Capacity Manual, Transportation Research Board, Washington, D.C.
- TUNG, R., WANG, Z., & CHIU, Y. C. Integration of Dynamic Traffic Assignment in a Four Step Model FrameworkA Deployment Case Study in Seattle Model. In Proc., Third Conference on Innovations in Travel Modeling.

- TZENG, G. H., & CHEN, C. H. (1993). Multiobjective decision making for traffic assignment. Engineering Management, IEEE Transactions on, 40(2), 180-187.
- US ENVIRONMENTAL PROTECTION AGENCY, 2009. Motor Vehicle Emission Simulator. MOVES 2010 User Guide. EPA report EPA-420-B-09-041, Office of Transportation and Air Quality, December 2009.
- VAN AREM, B., VAN DRIEL, C. J., & VISSER, R. (2006). The impact of cooperative adaptive cruise control on traffic-flow characteristics. *Intelligent Transportation Systems, IEEE Transactions* 7(4), 429-436.
- VASIRANI, M., & OSSOWSKI, S. (2010). A market-based approach to accommodate user preferences in reservation-based traffic management. Technical Report ATT.
- VICKREY, W., 1969. Congestion theory and transport investment. The American Economic Review 59(2), 251261.
- VOVSHA, P., B. DONNELLY, M. BRADLEY, J. BOWMAN, H. MAHMASSANI, T. ADLER, T., K. SMALL, D BROWNSTONE, K. KOCKELMAN, J. WOLF, & F. KOPPELMAN. (2012). Improving our Understanding of How Highway Congestion and Price Affect Travel Demand (No. SHRP 2 Capacity Project C04).
- WIE, B. W., TOBIN, R. L., FRIESZ, T. L., & BERNSTEIN, D. (1995). A discrete time, nested cost operator approach to the dynamic network user equilibrium problem. *Transportation Science*, 29(1), 79-92.
- YIN, Y., & LAWPHONGPANICH, S. (2006). Internalizing emission externality on road networks. Transportation Research Part D: Transport and Environment, 11(4), 292-301.

- YPERMAN, I., LOGGHE, S., & IMMERS, B. (2005, SEPTEMBER). The Link Transmission Model: An efficient implementation of the kinematic wave theory in traffic networks. In *Proceedings of the 10th EWGT Meeting, Poznan, Poland.*
- ZILIASKOPOULOS, A. K., & RAO, L. (1999). A simultaneous route and departure time choice equilibrium model on dynamic networks. *International Transactions in Operational Research*, 6(1), 21-37.
- ZILIASKOPOULOS, A. K., & WALLER, S. T. (2000). An Internet-based geographic information system that integrates data, models and users for transportation applications. *Transportation Research Part C: Emerging Technologies*, 8(1), 427-444.