Effects of autonomous vehicle ownership on trip, mode, and route choice

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ABSTRACT
Autonomous vehicles (AVs) may significantly change traveler behavior and network congestion. Empty repositioning trips allow travelers to avoid parking fees or share the vehicle with other household members. Computer precision and reaction times may also increase road and intersection capacities. As AVs are currently test-driving on public roads, they may be publicly available within the next two decades, within the span of 20 to 30 year planning analyses. Despite this, AV behaviors have yet to be incorporated into planning models. We present a multiclass four-step model including AV repositioning to avoid parking fees (but incurring additional fuel costs) and increasing link capacity as a function of the proportion of AVs on the link. Demand is divided into classes by value-of-time and AV ownership. Mode choice is between parking, repositioning, and transit using a nested logit model. Traffic assignment is based on a generalized cost function of time, fuel, and tolls. Results on a city network show that transit ridership decreases and the number of personal vehicle trips sharply increases due to repositioning. However, increases in link capacity offset the additional congestion. Although link volume increases significantly, only modest decreases in average link speed are observed.

Keywords: autonomous vehicles, planning, network modeling

1. INTRODUCTION

In the past two decades, autonomous vehicle (AV) research has been quickly maturing. With numerous developments in image recognition *(1)* and traffic detection and response systems *(2)* and spurred by competitions such as the DARPA challenge *(3)*, AVs now have legal permission to be driven on California and Nevada roads under the supervision of a test driver *(4)*. Although AVs are not currently available for purchase, they could be available at car dealerships in a decade or two. Some metropolitan planning organizations require 20 or 30 year predictions due to the long-term potential for roadway infrastructure investments, so AVs might be available during the time frame already under analysis. AV availability will provide travelers with additional benefits and options when driving. For instance, travelers may use laptops while traveling, or even have their AV drop them off at their destination then park elsewhere to avoid parking costs. However, vehicle miles traveled would increase per *traveler* trip. Also, this could result in a reduction in the number of transit trips because time spent in AVs in traffic may become less onerous and AV drop-off could avoid parking fees at the destination. Therefore, planning models should account for AV behaviors in their predictions.

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 *(5)* that could increase road network capacity when AVs are a significant share of the traffic. Another topic of interest is reduced following headways from cooperative adaptive cruise control (CACC) for connected vehicles (CVs) *(6)*, which could be incorporated into AVs as well. Furthermore, the NHTSA *(7)* specifies several levels of automation, ranging from none to full driving capability, with some partially automated vehicles currently available to the public. However, without more information on how these different levels of automation affect vehicle behavior, we focus on the differences between none and full automation.

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 *(8, 9)* 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 paper is to develop a modified 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 Greenshield's *(10)* speed-density relationship as the proportion of AVs increases.

This paper focuses on the AM peak, but the PM peak could be modeled using repositioning trips in the reverse direction (i.e. for picking up travelers from work). The four-step model was chosen because the greater simplicity of data inputs can more confidently be satisfied considering the lack of surveys on the topic. Also, many practitioners are still using the four-step model for their current planning applications, and therefore current data availability favors the four-step model.

The contributions of this paper 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 paper is organized as follows. §2 reviews literature on AV improvements to traffic operations and modeling approaches. §3 describes the generalized cost function and the §4 describes the modifications made to the four-step model to include the AV round-trip choice. §5 presents experimental results from the Austin downtown network, and conclusions are discussed in §6.

2. LITERATURE REVIEW

There does not appear to be any literature on planning models specifically for AVs at the date of this writing, although recent workshop presentations by Pendyala and Bhat *(8)* and Polzin et al. *(9)* indicate that the topic is under consideration. Studies by Dresner and Stone *(11, 12)* on intersection control policies taking advantage of the greater communications complexity and computer precision of AVs have demonstrated the potential for capacity improvements at intersections, even when compared against optimized signal timing *(13)*. Computer precision may similarly be applied to roads to reduce headways and increase capacity.

One development required for efficient planning analyses is a more macroscopic model of AV behaviors. Several city-wide models of AV intersection behavior have relied on custom micro-simulations, such as those by Carlino et al. *(14)* and Vasirani and Ossowski *(15, 16)*. Although these models include some form of traffic assignment in response to congestion, they do not yet incorporate user equilibrium (UE) principles, so their network congestion predictions may be based on less accurate routing strategies due to the high computation time incurred for solving UE. Although dynamic traffic assignment (DTA) includes UE principles, more study is required to modify the greater detail in DTA flow and intersection propagation for AV behaviors. A DTA model would be valuable, though, because of the potential improvements in modeling intersection delay. Therefore this paper uses a modified static traffic assignment, which can efficiently incorporate UE behavior.

Another potential network improvement from AVs is from the CACC technology developed for CVs *(6)*. CAAC has been shown to increased capacity through reduced safety margins for car following through microsimulation *(17)*. CAAC also increases stability and shockwave speed *(18)*, which may be considered in shared road DTA models. In the static traffic assignment (STA) –based planning model presented in this paper, we propose a heuristic for scaling capacity that retains a monotone travel time function.

Research into planning has mostly focused around two models: the four-step model *(19)*, and the more recent activity-based model (ABM) *(20)*. ABM may better predict repositioning trips because a major advantage to repositioning trips is sharing the car with other household members. However, although ABM is arguably a better predictor of current trips as well, many practitioners still use the four-step model because of the additional data and computational requirements of ABM *(21)*. As a result, research into the four-step model is ongoing; recent developments include work on integration with dynamic traffic assignment (DTA) *(22, 23, 24)*. For an initial planning analysis of AV behavior, the four-step model was chosen due to its greater simplicity and the additional complexities introduced in ABM. For instance, the impact of limitations in household car availability for all travelers on mode choice may be reduced by AV repositioning trips.

3. 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 paper 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's *(10)* 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.

3.1 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 *(11)* 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 *(20)* 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. 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. *(25)* and Yao and Song *(26)*, 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 STA model is used with four-step planning. Although Tung et al. *(22)* and Duthie et al. *(24)* 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's *(10)* 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 Travel time 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:

(1)

where is travel time when the flow is , flow specific to class is , is the free flow travel time, is the capacity, and and are calibration constants for link .

Since the VOT varies across the population, the population of travelers is instead divided among a set of discrete classes , with each having a VOT of . Each class uses AVs entirely, or not at all, denoted by the boolean variable . 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 the conditions under which is monotone increasing with respect to any . This is necessary but not sufficient for convexity in a multiclass formulation (Marcott and Wynter, 2004).

(2)

therefore if

(3)

Equation (3) implies that capacity must exceed the change in capacity due to vehicles; otherwise may decrease resulting in a decrease in .

A capacity function based on the well-known Greenshields's *(10)* speed-density relationship and an increasing jam density function of the proportion of autonomous vehicles is shown to satisfy (3) under reasonable assumptions. Greenshields' relationship predicts

(4)

where is vehicle speed, is free flow speed, is density, and is jam density. Based on equation (4), capacity is , a linear function of jam density. Therefore in the BPR function was also assumed to be a linear function of jam density:

(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 including length of the vehicle ahead, with AVs requiring a distance , both measured in feet. Jam density is then

(6)

in units of vehicles per mile.

The capacity function defined by equations (5) and (6) is shown to be monotone increasing with respect to any under the assumption that . This assumption is reasonable considering highway vehicle spacing at jam density was estimated at feet for one city by Van Aerde and Rakha *(27)*, and Elefteriadou et al. *(28)* suggests feet length for a passenger car equivalent, which is a lower bound on spacing.

From , , so . Since ,

(7)

Since capacity can be rewritten as

(8)

then

(9)

simplifies to

(10)

which is satisfied because equation (7) is true □

3.3 Cost function

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. *(29)*, based on a regression equation from MOVES *(30)* data, was used:

(11)

where is vehicle speed in miles per hour and is energy consumption in kilo-Watt hours per mile. 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, , which was assumed to be constant for the network. For a link (where is the set of links) with length in miles, the fuel consumed over the link for a travel time of in hours, , is then

(12)

where 36.44 is the energy content of gasoline *(31)*.

When creating generalized costs based on travel time and money, an important variable is the VOT for conversion to a single unit, denoted by for class . 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 , is a combination of travel time, fuel consumption, and road toll :

(13)

For a parking fee of , the cost of a one-way driving trip from to followed by parking is

(14)

where is the route.

For the return leg of AV round-trips, with no passenger, travel time is not a factor, so the notation with is used to denote the cost of driving with VOT. Cost of an AV round-trip, using path for travel from to and path for travel from to , is

(15)

The cost of traveling on link using transit is similarly

(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

(17)

where is the transit fee for traveling from to . Multimodal routes are not permitted in this model.

3.4 Traffic assignment

The traffic assignment formulation is multi-class because of the distinction between AV and non-AV vehicles. Marcott and Wynter *(32)* demonstrate 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's *(32)* 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 (22) as a heuristic for the VI of equation (18) 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 *(33)*.

Multiclass user equilibrium assignment with fixed demand was formulated as a variational inequality (VI) in the form of Nagurney and Dong *(34)*. Let be the vector of all class link flows. The VI problem is to find such that

(18)

where is the vector of class-specific driving costs and is the feasible region defined by

(19)

(20)

(21)

satisfies user equilibrium due to Nagurney and Dong's *(34)* proof on a more general form of this VI incorporating elastic demand and OD disutility. Due to the special behaviors of AVs, we include only assignment in the VI and consider travel demand separately as trip distribution and mode choice in the four-step model.

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

(22)

where is the search direction, for . This appeared to converge for a city-size network, as shown in Figure 1. The algorithms for multiclass VI formulations of traffic assignment studied by Nagurney and Dong *(34)* and Marcott and Wynter *(32)* may improve convergence. Optimal convergence of traffic assignment was not a major focus of this study, and a specific algorithm is not a requirement of the model.

4. PLANNING MODEL

The commonly used four-step model was modified to incorporate AV round trips. The latter 3 steps incorporated a feedback element for convergence to a stable solution. The following subsections discuss trip distribution and mode choice in greater detail. Multiclass traffic assignment was formulated in §3.4.

4.1 Trip generation

The first step is trip generation, which determines productions and attractions based on survey data for each , , where is the set of zones. Productions and attractions for each zone are vectors in to distinguish between VOT classes. Although the distribution among VOT classes may vary at each zone, system-wide consistency of is required.

4.2 Trip distribution

Trip distribution determines the number of person trips between every OD pair , which is assumed to increase with productions and attractions and decrease with travel cost. As with trip generation, to distinguish between VOT class. Minimum cost used for determining person-trips is defined as

(23)

Then

(24)

where is the decreasing friction function, , and is adjusted iteratively to for consistency with productions and attractions, .

4.3 Mode choice

Mode choice splits the person trips per origin-destination into mode-specific trips per mode , with 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 is included. denotes the traveler preference for transit.

Mode-specific trips per class are therefore defined as

(25)

(26)

(27)

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

(28)

4.4 Four-step algorithm

The standard four-step algorithm with feedback as described in McNally *(19)* 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 be the person-trips and be the trips using mode from to at iteration of the feedback loop, and and be the search direction at iteration . A step size of is used, i.e.

(29)

(30)

Convergence was measured based on the root mean squared error of mode-specific trips as suggested by Boyce et al. *(35)*:

(31)

The AV four-step model was observed to converge on the downtown Austin city network.

5. EXPERIMENTAL RESULTS

The model was tested on the Austin downtown sub-network with 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, 62836 trips, and 84 bus routes.

Due to lack of VOT distribution data per zone, the same distribution (shown in Table 1) was used for each zone with VOTs ranging from 1.15 to 22. Values of time were uniformly chosen from a range, and the log-normal expression with mean and standard deviation

(32)

was used to determine the class distribution of demand as suggested by Yang and Meng *(36)* and Huang and Li *(37)*. The inverse friction function – was used. 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. As with Pool et al. *(21)*, . was set as to avoid artificial inflation of the modal split.

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 in decreasing order by , and running experiments. On the th experiment, the first classes of this ordering of were assumed to use autonomous vehicles.

5.1 Convergence of traffic assignment

Because of the multiclass formulation, the traffic assignment VI does not necessarily have a unique or existent equilibrium, and the common 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 equilibria. Figure 1 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.

5.2 Reduction in transit demand

Figure 2 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 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 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 2 and 3).

5.3 Autonomous vehicle demand

AV round-trip demand was a high fraction of the total personal vehicle demand, reaching 83% at full market penetration (Figure 3). This analysis 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.

5.4 Long-term effects

Table 2 shows the mode split for each VOT class before any AVs and after full AV availability, and Table 3 shows the mode disutility per class in units of dollars. Because of the model definition and parameters, the difference between parking and round-trip disutilities is the difference between parking costs and fuel costs. Travel time has an identical effect on both parking and round-trip because the traveler is only in the vehicle going to the destination. In the absence of data, the traveler preference for parking and round-trip was set identical to avoid artificially skewing the modal split. Total demand for any personal vehicle mode changed from 23500 person trips to 47676 trips, and with the shift to 39592 AV round-trips, the total number of trips made by personal vehicles increases to 87275 – 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 4. This is encouraging because it suggests that the increases in demand are substantially offset by increases in capacity from AVs.

5.5 Effect on traffic

Figure 4 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-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. However, 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.

6. CONCLUSIONS

This paper 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 Greenshields's *(10)* speed-flow 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 with these repositioning trips to the origin 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, increases in travel times were offset by the road capacity increases of AV use.

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 round-trips 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.

Another group likely to be affected is parking garage owners, who will have to reduce costs to remain competitive against the cost of additional fuel consumption for an AV round-trip. The effect of parking price reductions in response to lower demand was not modeled, and should be studied in future work. As an initial model for modeling the effect of AVs on demand, this paper made many simplifying assumptions that should be relaxed in future work. Additionally, uniqueness of user equilibrium could not be proved due to the multiclass formulation. The magnitude of observed modal changes may depend on mode and active transportation options in the model. For comparison, the model should be studied on regional networks and networks with additional transit options. Furthermore, partial automation as specified by the NHTSA may be available sooner yet have similar effects on traffic flow. Different levels of automation should be studied in future work. Nevertheless, this model is a starting point for future models, and suggests that transit demand will likely experience a significant decrease after generally affordable autonomous vehicles are introduced.

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TABLE 1 VOT distribution

Class	**VOT**	**Share**
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 2 Comparison of mode-specific demand before AV availability and after full AV availability.

VOT	Demand without AVs			Demand with AVs		
	Park	Transit	Round-trip	Park	Transit	Round-trip
1.15	3.10%	96.90%		1.40%	49.00%	49.60%
3.5	15.20%	84.80%		6.10%	33.00%	60.90%
5.85	41.40%	58.60%		15.10%	19.60%	65.40%
8.15	64.10%	35.90%		20.90%	12.00%	67.10%
10.5	78.90%	21.10%		24.30%	7.80%	67.80%
13	88.00%	12.00%		26.60%	5.30%	68.10%
15	92.30%	7.70%		27.80%	3.90%	68.20%
17.5	95.50%	4.50%		28.90%	2.80%	68.30%
20	97.30%	2.70%		29.60%	2.10%	68.30%
22	98.20%	1.80%		30.00%	1.70%	68.20%

TABLE 3 Comparison of mode and class specific costs (in dollars) before AV availability and after full AV availability

VOT	Disutility without AVs				Disutility with AVs		
	Park	Transit	Round-trip		Park	Transit	Round-trip
1.15	5.94	2.04	2.67		6.05	1.99	0.57
3.5	6.06	3.85	2.58		6.33	3.75	0.79
5.85	6.2	5.73	2.6		6.63	5.54	1.01
8.15	6.34	7.66	2.67		6.92	7.31	1.22
10.5	6.48	9.64	2.71		7.23	9.13	1.44
13	6.64	11.72	2.73		7.56	11.08	1.67
15	6.75	13.38	2.73		7.82	12.63	1.86
17.5	6.9	15.42	2.73		8.15	14.56	2.09
20	7.04	17.45	2.73		8.47	16.49	2.33
22	7.16	19.06	2.73		8.73	18.04	2.52

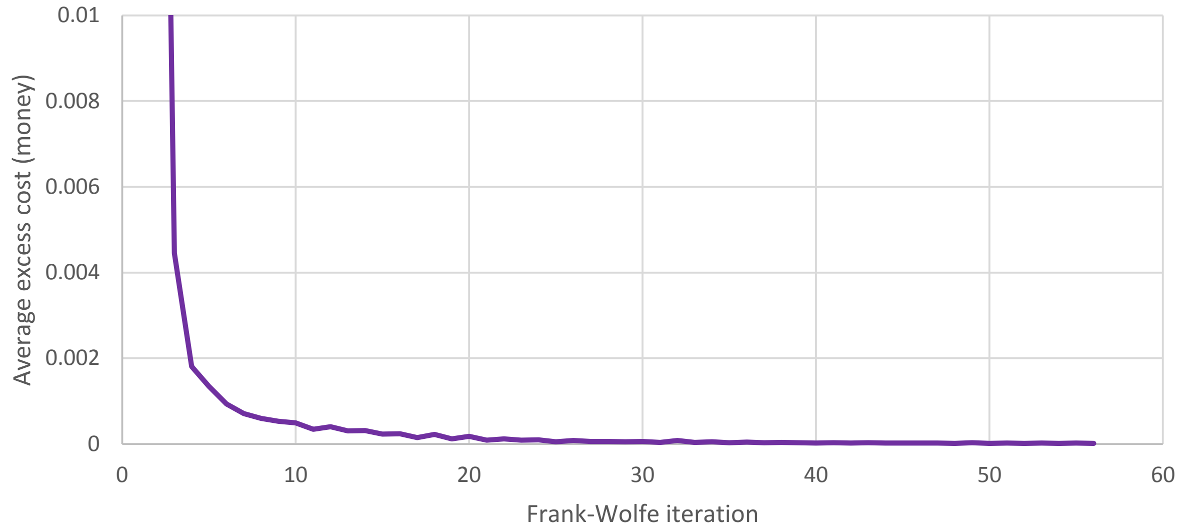

Figure 1. Convergence of traffic assignment.

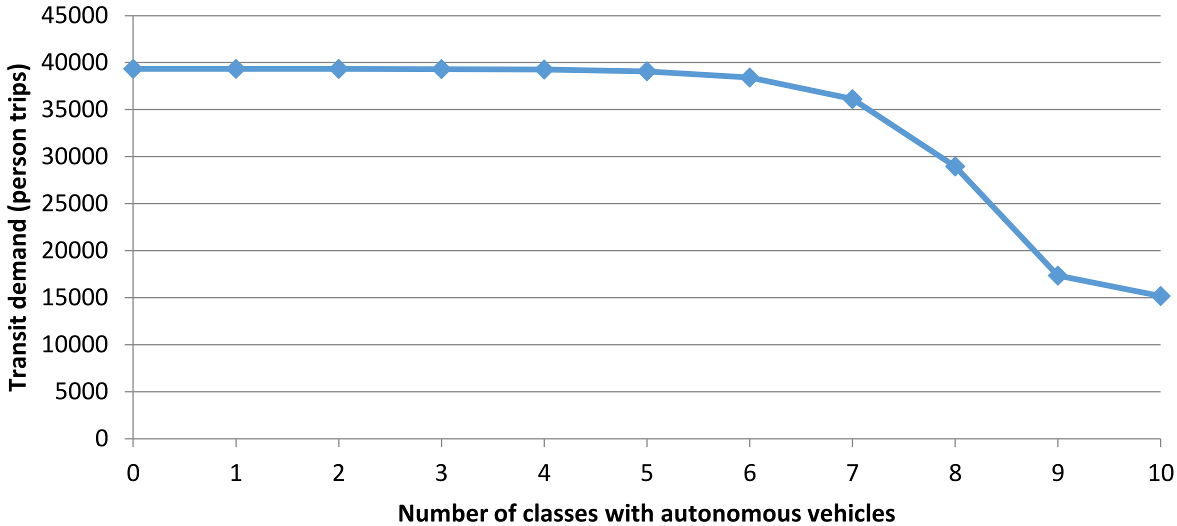

FIGURE 2 Total transit demand

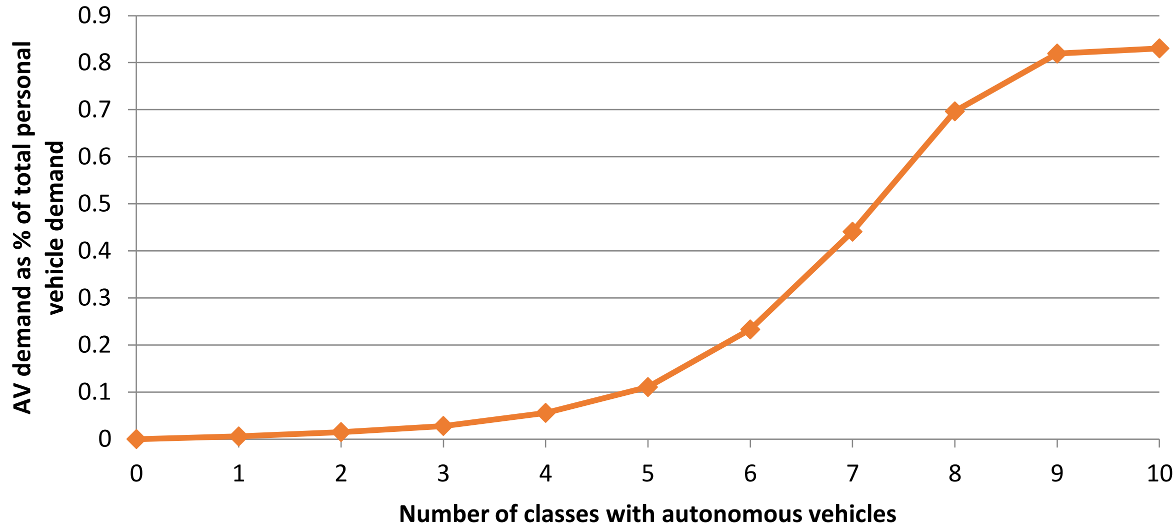

FIGURE 3 AV round-trip demand as a percentage of total personal vehicle demand

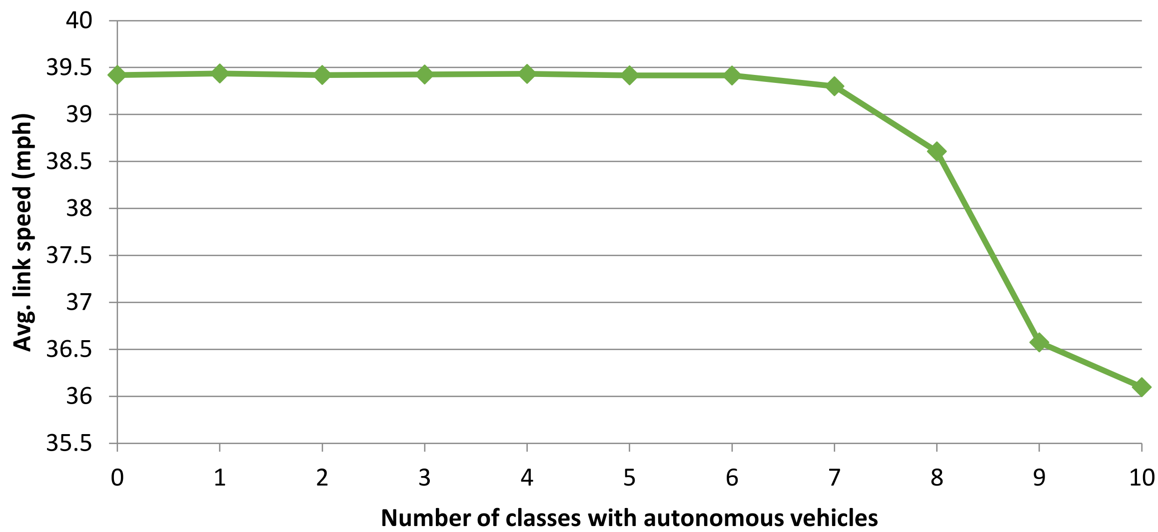

FIGURE 4 Change in average link speed, weighted by length, as AV availability increases