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Travel Modeling in an Era of Connected and Automated Transportation Systems: An Investigation in the Dallas-Fort Worth Area

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16. Abstract
The field of transportation modeling has seen many advances in recent years with approaches involving activity-based modeling and agent-based simulations. There have also been advances to the traditional four-step model, with researchers developing faster and more efficient sub-models. The basic structure of the four-step model, however, has remained fundamentally the same: trip generation, trip distribution, mode choice, and trip assignment. The long-lasting nature of this structure speaks not only to the model's flexibility, but also to its transparency and (comparative) ease of use.

Recent technological developments have led to the creation of whole new modes of transportation, such as ride-hailing services. Furthermore, the advent of self-driving automated vehicles (AVs) seem to be a tangible and concrete possibility the near future. In light of these changes, transportation agencies need to review and update their models to more accurately analyze future scenarios and plan accordingly.

The main objective of this report is to document the changes made to the North Central Texas Council of Government's (NCTCOG) four-step model in order to accommodate those two new features: ride-hailing services and AVs. Chapter 1 contains a review of recent literature on the subject, including projections made by several researchers. Chapter 3 presents the general modeling framework, while Chapter 4 contains more detailed documentation on actual changes made to the NCTCOG's TransCAD/GISDK codes. Chapter 5 contains simulation results from the new models. Finally, Chapter 6 contains closing remarks on the process so far and points to new directions for further modifications.

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Table of Contents

List of Figures

List of Tables

Chapter 1. Project Overview

The field of transportation modeling has seen many advances in recent years with approaches involving activity-based modeling and agent-based simulations. There have also been advances to the traditional four-step model, with researchers developing faster and more efficient sub-models. The basic structure of the four-step model, however, has remained fundamentally the same: trip generation, trip distribution, mode choice, and trip assignment. The long-lasting nature of this structure speaks not only to the model's flexibility, but also to its transparency and (comparative) ease of use.

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Chapter 2. Literature Review

2.1 Introduction

Transportation planning typically relies on an iterative modeling process that considers the inter-dependencies of travel demand and the performance of multi-modal transportation networks on which travel occurs. The traditional planning process considers a four-step process that consists of separate models to estimate trip generation, trip distribution, mode choice and route assignment. There is a growing belief that the traditional methods used for performing these four steps may be unsuitable for forecasting the traffic more than 10 years from now. This is because there is considerable uncertainty regarding how transportation systems will operate in the future with the introduction of autonomous and connected vehicle technologies. These technologies will have an impact on every step in the four-step model.

Transportation that is more efficient, cheaper and convenient (devoid of the hassle of driving) may have an incremental effect on trip generation. At the same time, advances in areas other than transportation such as augmented reality and virtual reality may cause a reduction in transportation as working and socializing becomes easier to do from home in a virtual environment. Even when transportation is required, the convenience of AV travel may promote more individuals to live farther from the urban center.

The high cost of purchasing an AV combined with the low cost of operation makes AVs more suitable for use in ride-hailing than for ownership. The concept of Mobility-as-a-Service has been gaining traction in recent years. The low cost and reliability of using AV based ride-hailing will further mobility being viewed as a service.

Information regarding travel times and road conditions gathered and shared by connected vehicles will make it easier for individuals or algorithms in routing systems to make optimal decisions regarding route choice. Complex traffic rules can be implemented if vehicles in the traffic are autonomous as they can perceive and react instantaneously. Advanced traffic control systems and tolling mechanism can add a new layer of complexity to how autonomous vehicles decide on which routes to take. Without the human element, the operation of vehicle fleets can be much more strategic and coordinated. As a result, they may be more efficient in meeting traffic demand with less number of vehicles. The improved coordination combined with precise information can further improve the efficiency of the system.

This document provides a summary of several studies that have been conducted in trying to understand the impact disruptive technologies such as connected and autonomous vehicles (CAV) will have on travel demand and supply. The impact on mobility of these technologies will occur from the following fronts:

1. Travel demand
2. Network Capacity
3. Market Penetration
4. Ride-hailing Operation
5. Current MPO practices

2.2 Travel Demand

AVs are expected to reduce many of the inconvenience that are associated with traveling by non-AVs. The stress of driving through congested roads is eliminated and the time spent inside the car can be utilized for more productive or relaxing pursuits. The trouble of finding a parking spot can also be delegated to the vehicle. These conveniences make AV travel modes superior to most of the existing modes and this in turn would increase the overall travel demand.

One of the main reasons individuals choose transit over a private vehicle is unavailability of parking. Once AVs become commonplace, unavailability of parking will no longer be a significant deterrent to traveling by a private vehicle. The AV can be asked to reposition itself to a suitable location once the passengers have been dropped off. This will lead to more number of trips using private vehicles and reduce the mode share of transit. However, the increased congestion because of more trips by private vehicles and repositioning of empty vehicles would increase cost of trips because of the extra fuel consumption. This will offset some of the reduction in transit mode share (Levin and Boyles, 2015). Also the use of autonomous vehicles for first and last mile commute can further improve the prospect of transit (Scheltes and de Almeida Correia, 2017; Shen et al., 2017). Cities such as Los Angeles have already revealed plans to incorporate autonomous pods to provide last mile connectivity for transit (Walker, 2016).

The number of trips by cars may increase not just because of mode shift from other modes such as transit but also because of increased mobility. Certain demographics such as senior citizens, individuals below the age of 18 and differently abled citizens will make significantly more number of trips as they will experience a much higher improvement in mobility. Quantification of the number of such additional trips has been attempted in Truong et al. (2017).

The increased convenience and the possibility of spending time more productively in an autonomous vehicle would make individuals more tolerant of higher in-vehicle travel times. To model this fact, it has been suggested in literature to apply a Value of Time (VOT) reduction factor when computing mode utilities. The range of VOT reductions is generally between 25% and 35% (Childress et al., 2015; Kröger et al., 2016).

Although the convenience of traveling via AVs may have an incremental impact on travel demand, it cannot be concluded that the overall travel demand will increase. Several technologies are under development which would reduce our need for travel. Promoters of technologies such as Augmented Reality (AR) and Virtual Reality (VR) promise to virtually provide the experience of meeting in person or exploring travel destinations without leaving the comfort of the living room. If the experience from these technologies hold up to their promise it may reduce the need to make trips for commuting, socializing or sightseeing. However, the determining the effects of these technologies is outside the scope of this project. It was predicted in the 1980s that advances in telecommunications would decrease commuting drastically, but this never materialized (Rosalsky, 2017). Another technology that could impact travel demand is delivery by drones (Martin Joerss et al., 2016).

2.3 Network Capacity

Infinitesimally small reaction times and better awareness of its environment because of an array of sensors and vehicle-to-everything (V2X) communication allows CAV to utilize road space much more efficiently than human drivers. Several technologies have been conceptualized and some have already been implemented which can improve the safety and travel times of CAVs.

Automated Cruise Control (ACC) allows vehicles to follow its lead vehicles without any human intervention. Two parameters that are set before the activation of this feature are desired speed and minimum headway. The ACC enabled vehicle maintains the desired speed when it is unobstructed by any vehicle. When obstructed by a slow moving vehicle, it maintains the minimum time headway with the vehicle in front. Okamura et al. (2011) showed that vehicles with ACC improves traffic safety. But the impact of ACC on highway capacity depends on the minimum headway parameter. At low values of minimum time headway, the capacity may improve but in the more general case, the highway capacity is expected to reduce since conservative headways may be used to ensure safety (Okamura et al., 2011; Vander Werf et al., 2002). It has also been shown that ACC vehicles, like human driven vehicles, may not be string stable (Sheikholeslam and Desoer, 1990). String stability gives a measure of the ease with which perturbations in the speed of a vehicle can propagate through a string of vehicles. Lower string stability results in the increased occurrence and severity of phantom traffic jams which negatively impacts road capacity.

Cooperative Adaptive Cruise Control (CACC) is an advanced version of ACC which also used Vehicle-to-Vehicle (V2V) communication. Because of V2V, a vehicle with CACC not only knows the speed and position of the vehicle in front, but of all the vehicles within a short radius of it. In effect, CACC enabled vehicles can "see" beyond just the vehicle in front. Therefore, these vehicles can afford to maintain shorter time gaps with the vehicles in front (Vander Werf et al., (2002) uses a time gap of 0.5 second). Vehicles with CACC improve traffic capacity and traffic stability (Delis et al., 2015; Milanés and Shladover, 2014; Talebpour and Mahmassani, 2016; Tientrakool et al., 2011; van Arem et al., 2006). Vehicle platooning can be considered as an application of CACC technology.

The current system of traffic signals and signs are designed for human drivers. More complex and efficient intersection management systems can be implemented if all the vehicles in traffic are CAVs. Autonomous Intersection Management (AIM) is one such system that was conceptualized by Dresner and Stone (2005, 2004). In this system, AVs call ahead to reserve time-space slots to pass through an intersection. A centralized agent called the intersection manager receives all the reservation requests from vehicles and allots time slots to them in a manner that there is no conflicting vehicle movement. Since all vehicles are autonomous, these space time slots can be quite narrow resulting in a much more efficient use of space. A simulation conducted by Dresner and Stone (2005) shows that at moderate traffic volumes, this system can be as efficient as an overpass.

If movements of CAVs are programmed to dampen traffic waves, road capacity can be improved. Stern et al. (2017) shows how 5% of vehicles being CAVs can dampen stop-and-go traffic waves. Talebpour et al., (2016) studies the effectiveness of speed harmonization algorithms when implemented using Dedicated Short Range Communication (DSRC).

2.4 Market Penetration

Penetration rates can, in a general sense, be studied in three different ways: percentage of the whole fleet of vehicles owned by the population; percentage of new cars sold; and percentage of trips.

Bansal and Kockelman (2017) compile the main literature regarding the adoption of autonomous vehicles and also provide their own estimates. Tables 1, 2, and 3 summarize their findings in terms of the three aforementioned types of penetration rates.

Table 1 Penetration rates - Vehicle Ownership

Paper	Automation	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060
Laslau et al. (2014)	Level 2				92%						
Laslau et al. (2014)	Level 3				8%						
Morgan Stanley (2013)	Level 3				100%						
Rowe (2016)	Level 4										100%
Morgan Stanley (2013)	Level 4									100%	
Bierstedt et al. (2014)	Level 4					25%					
IHS Automotive (2014)	Level 4								100%		
Litman (2017)	Level 4		1-2%		10-20%		20-40%		40-60%		

Table 2 Penetration rates – New Vehicles Sold

Paper	Automation	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060
Litman (2017)	Level 4		2-5%		20-40%		40-60%		80-100%		
ABI Research (2013)	Level 4					50%					
Mosquet et al. (2015)	Level 4					10%					
Alexander & Gartner (2014)	?					75%					

Table 3 Penetration rates - Trips

Paper	Automation	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060
Litman (2017)	Level 4		1-4%		10-30%		30-50%		50-80%		
Hars (2014)	Level 4				90%						

Bansal and Kochelman (2017) note that the existing literature has only a few such forecasting studies by academic researchers, with most studies conducted by consulting firms, investment banks, and other private enterprises, most of which do not focus on the forecasting methods used in their reports.

Besides compiling information regarding penetration rates, Bansal and Kochelman (2017) also generated their own estimates, as presented in Table 4.

Table 4 Penetration rates from Bansal & Kochelman

Scenario	Automation	2015	2020	2025	2030	2035	2040	2045
Scenario 1	Level 3	0.0%	2.1%	4.6%	7.6%	8.3%	8.0%	10.4%
Scenario 1	Level 4	0.0%	3.9%	11.1%	19.7%	28.6%	37.0%	43.0%
Scenario 2	Level 3	0.0%	3.0%	5.3%	7.7%	8.7%	7.9%	13.7%
Scenario 2	Level 4	0.0%	3.0%	10.2%	19.0%	28.7%	37.9%	43.8%
Scenario 3	Level 3	0.0%	1.9%	3.2%	4.5%	6.5%	8.1%	8.9%
Scenario 3	Level 4	0.0%	2.0%	5.2%	10.3%	15.0%	19.2%	24.8%
Scenario 4	Level 3	0.0%	2.7%	5.1%	7.5%	8.7%	8.2%	13.9%
Scenario 4	Level 4	0.0%	2.9%	10.2%	18.8%	28.5%	36.3%	43.4%
Scenario 5	Level 3	0.0%	2.3%	5.3%	8.1%	8.5%	8.3%	8.2%
Scenario 5	Level 4	0.0%	3.3%	10.8%	19.0%	27.2%	35.9%	43.2%
Scenario 6	Level 3	0.0%	2.1%	6.1%	8.4%	8.5%	28.6%	16.3%
Scenario 6	Level 4	0.0%	4.7%	15.1%	27.2%	38.3%	45.7%	70.7%
Scenario 7	Level 3	0.0%	2.5%	5.9%	8.3%	8.2%	26.5%	25.5%
Scenario 7	Level 4	0.0%	4.7%	13.8%	25.5%	36.4%	44.3%	59.7%
Scenario 8	Level 3	0.0%	3.5%	6.0%	7.7%	27.7%	11.6%	2.9%
Scenario 8	Level 4	0.0%	5.5%	19.4%	33.8%	44.2%	74.7%	87.2%

One of the most cited works on the topic of market penetration of AVs is from Litman (2017), where he generates predictions for level 4 AV penetration, presented Table 5 and Figure 1.

Table 5 Level 4 AV predictions from Litman (2017)

Autonomous Vehicle Implementation Projections

Stage	Decade	Vehicle Sales	Veh. Fleet	Veh. Travel
Available with large price premium	2020s	2-5%	1-2%	1-4%
Available with moderate price premium	2030s	20-40%	10-20%	10-30%
Available with minimal price premium	2040s	40-60%	20-40%	30-50%
Standard feature included on most new vehicles	2050s	80-100%	40-60%	50-80%
Saturation (everybody who wants it has it)	2060s	?	?	?
Required for all new and operating vehicles	???	100%	100%	100%

Autonomous vehicle implementation will probably take several decades.

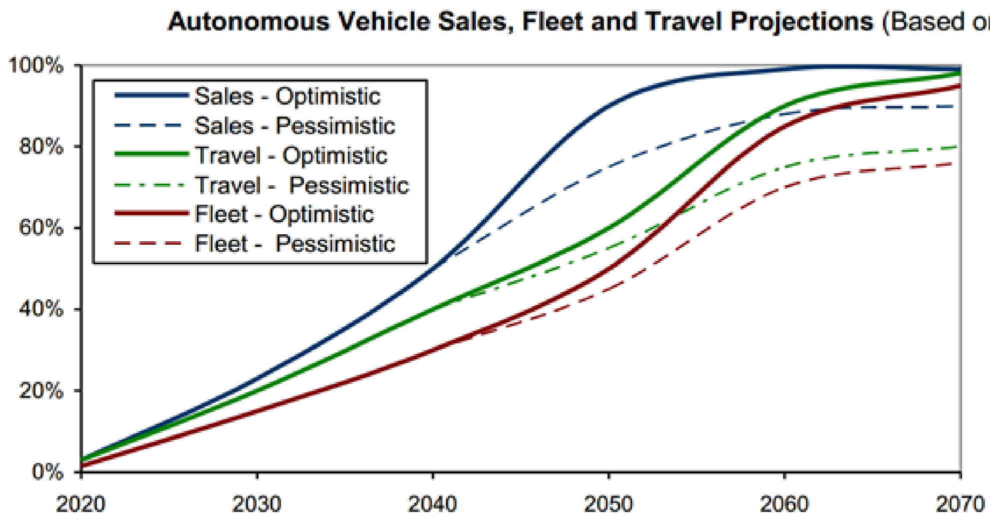

Figure 1 Projections for level 4 AVs from Litman (2017)

We can now use these multiple AV penetration rates proposed by experts and create "optimistic" and "pessimistic" scenarios. The overall proportions can then be used to calibrate AV adoption models on a disaggregate household level. Finally, we can initiate the Four-step process in parallel for both households with and without AVs.

2.5 Ride-hailing Operation

Many sectors of the world of transportation are interested in studying ride-sourcing services. There is, however, very scarce peer-reviewed literature on the matter, likely due to the fact that these markets are very recent. One statistic regularly cited to illustrate both, the disruptive power and emerging nature of these services, is the fact that it took Uber, the largest TNC, six years to reach the one billion trip milestone in 2015, but only six additional months to reach the two billion milestone; currently, the company has exceeded 5 billion trips (Uber, 2017).

The highly exponential nature of the service's growth in recent years makes predictions of future ride-sourcing trends quite difficult. Furthermore, the possibility of incorporating autonomous vehicles into their fleets also likely affect the real usage of these services in the future. Yet another layer of complexity is understanding what paradigm will prevail: private or shared economy.

The few studies that do exist refer mainly to the service users' characteristics and to controversies regarding the services' fairness in competing with taxis.

Regarding the taxi/ride sourcing controversy, Rayle et al. (2016) points out that taxis have directed significant criticism towards ride sourcing companies because they see them as "an illegal service that flouts existing laws and competes unfairly".

In an analysis of ride sourcing users in the Puget Sound region, Dias et al. (2017) note that younger, richer, employed people with smartphones, higher education levels, and fewer vehicles tend to have higher propensities to use ride sourcing services. Using the same dataset, Lavieri et al. (2017b) analyzed the determinants of ride-hailing adoption (as a sub component of a larger model), and found that living in high residential density areas and having a tech-savvy life-style were important contributing factors that encouraged the adoption of ride-hailing. Lavieri et al. (2017a) focused their attention on Austin, Texas, and estimated that regions that have a higher male population proportion are more likely to have at least one ride sourcing trip during the weekday and no ride sourcing trips during the weekend days. Unsurprisingly, zones with high vehicle ownership rates are more likely to have no ride sourcing trips during weekdays, while zones that have parks are less likely to have zero trips generated during weekends. There have been very few studies that analyze the network-level impacts of ridesourcing. Levin et al. (2016) modify the classic 4 step model structure to incorporate shared autonomous vehicles, which in this context, can be seen as ridesourcing services that use AVs. Even though they found that the AV ridesourcing system was highly effective at reducing congestion, their results are somewhat difficult to generalize for the case with ridesourcing services that use non-AVs.

One possibility of incorporating ridesourcing in the traditional 4 step modeling procedure is by creating parallel procedures for the first three steps exclusively for ridesourcing trips. In that case, we would perform trip generation and distribution for these trips using currently available data. Mode choice would not be necessary for these trips since they are already mode-specific. Finally, the trip matrices can be incorporated into the traffic assignment stage. Assumptions can also be made about how ridesourcing drivers are repositioned between trips.

2.6 Current MPO Practices

Guerra (2016) explores the extent to which MPOs have considered the impact of AVs on their long-range regional transportation plans (LRTP). Guerra explains that most MPOs have not considered AVs in their current RTPs mainly. The main reasons for this are,

- High uncertainty regarding the effects of the technology
- Potential impact of AVs are too far removed from decisions about where and how to invest in transportation infrastructure
- AVs are just one of several other factors which can impact traffic such as improvement in telecommunication, climate change polices and federal funding.

We attempted to contact 3 MPOs: the New York Metropolitan Transportation Council (NYMTC), Puget Sound Regional Council (PSRC) and Los Angeles County Metropolitan Transportation Authority (LA Metro) to enquire about how these MPOs have accommodated impact of AVs on their travel forecasts. NYMTC responded that they are currently not incorporating these effects into the model as AVs are not yet legal in the state and their future is uncertain. The other 2 MPOs had not responded. However, the recent paper (Childress et al., 2015) may be an indication of the direction in which PSRC is predicting the impact of AVs (The author Suzanne Childress is a principal travel modeler at PSRC).

According to Guerra (2016), MPOs of Atlanta, San Francisco and Seattle (PSRC) have attempted to incorporate AVs into their existing models. The results from these models are summarized in Table 6. These model results were obtained by altering parameters in their existing activity based models. Childress et al. (2015) cautions that such an approach stretches the capabilities of the activity-based models.

Table 6 Impact of AVs on VMT predicted by MPOs using their activity-based planning model

Region	In-vehicle Time Costs	Road Capacity	VMT Change	Key Assumptions
Atlanta	Zero	+50%	+3.6%	
	50% of car	+50%	+12.7%	
	50% of car	+50%	+23.8%	Reduced operating costs
	50% of car	+50%	+23.9%	Reduced operating costs and free parking
San Francisco	Same as car	+100%	+2%	All scenarios: driver present, though interventions rare; no intercity travel; same car ownership levels and urban form
	High-quality rail	+10% to +100%	+4% to +5.2%	
	50% of car	+10% to +100%	+6.7% to +7.9%	
	Zero	+0% to +100%	+13.2% to +14.5%	
Seattle	Same as car	+30%	+3.6%	
	65% of car	+30%	+5.0%	Owned by high-income households only
	65% of car	+30%	+19.6%	50% parking cost reduction
	Zero	+0%	−34.5%	No car ownership. Cost is $1.65 per mile.

Sources: Childress et al. (2015); Michael Gucwa (2014); Kim et al. (2015).
Note: MPO = metropolitan planning organization; VMT = vehicle miles traveled.

Source: Guerra (2016)

The impact AVs and related new technologies are likely to have on difference stages of the planning process is summarized in Table 7.

Most of the papers focus on the impact AVs have on certain aspects of traffic modeling. Some aspects such as trip distribution and modeling of ride sharing are relatively underrepresented in the literature. There are very few papers which provide a holistic analysis of the impact of AVs on travel. However, the methodologies and assumptions presented in these papers will be valuable in developing better models to predict the impact of AVs.

Table 7 Impact of AVs on different stages of the planning process

Step	Impacts
Trip Generation	• Increased convenience of travel boosts demand • Significant improvement in mobility for certain demographics such as senior citizens, people with disabilities and children • Ease of parking • New technologies such as augmented reality, virtual reality and delivery by drones and AVs
Trip Distribution	• Increased travel convenience may cause individuals to live further away from city centers decreasing urban density • The presence of high utility AV based mobility services may increase the attractiveness of living in cities
Mode Choice	• Convenience of travelling in AVs decrease the perceived value of time for these modes • The option of parking further for AV users also affect mode choice
Assignment	• Technologies such as CACC enable vehicles to maintain lower headways at higher speeds increasing traffic capacity • Communicating with traffic infrastructure such as traffic lights can further boost capacity • Some technologies such as ACCs may decrease traffic capacity depending on how they are implemented. • Increased travel demand may lead to more congestion and lowering of network capacity

Chapter 3. Modeling Framework

3.1 Introduction

In this chapter we propose a modeling strategy, within the framework provided by NCTCOG's current planning model, to capture the impact of new mobility services and technologies, such as ride-hailing (e.g. Uber, Lyft and other comparable services) and connected/autonomous vehicles (CAVs/AVs). This strategy is composed of a series of modifications to the existing four-step planning model, which normally consists of 1) Trip Generation, 2) Trip Distribution, 3) Mode Choice and 4) Traffic Assignment. Figure 2 presents the general structure of the proposed changes to the existing methodological approach.

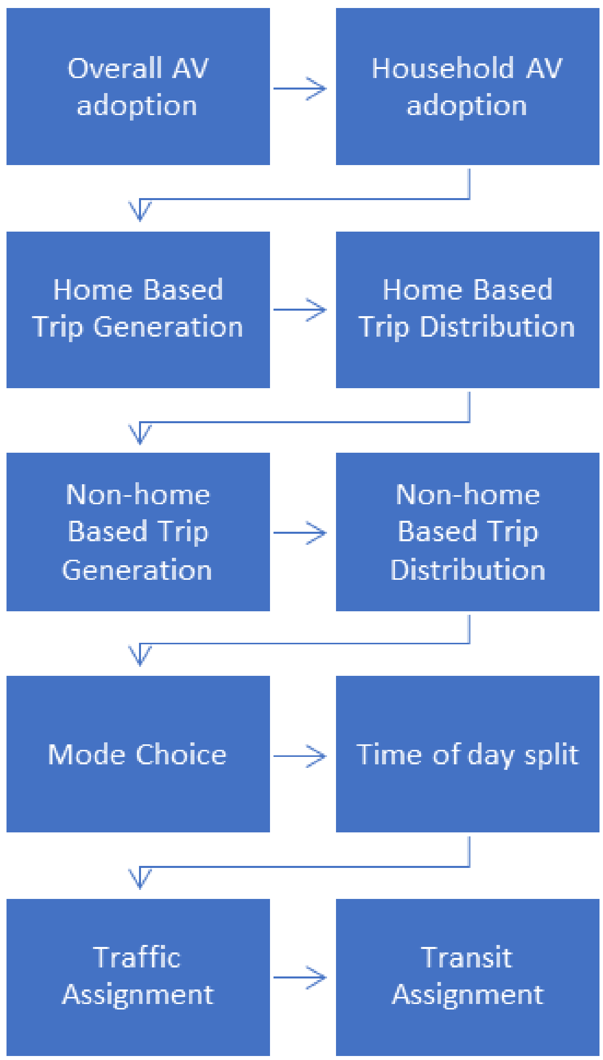

Figure 2 Model diagram

In the following sections, we describe each of these models and the alterations being proposed.

3.2 Overall AV Adoption

The initial step in our methodology produces an estimate of the overall AV adoption by network users, also known as the "penetration rate," for a desired year or scenario. This penetration rate will control how many households will be modeled as AV adopters and, therefore, prone to generating trips with AVs. The remaining households without AVs will only generate trips using regular human-driven vehicles.

Bansal and Kochelman (2017) compile the main literature regarding the adoption of autonomous vehicles and also provide their own estimates in terms of the three types of penetration rates: 1) percentage of the whole fleet of vehicles owned by the population, 2) percentage of new cars sold, and 3) percentage of trips, respectively. They note that the existing literature has only a few such forecasting studies by academic researchers, with most studies being conducted by consulting firms, investment banks, and other private enterprises. The majority of these entities do not report the forecasting methods used in their reports.

Due to the wide disparity in available predictions of actual AV adoptions for the future, the current modeling efforts will not try to forecast these values. Instead, the approach used will be closer to sensitivity analysis, where certain arbitrary AV adoption values of interest will be used, such as 20% and 30%. The other parts of the model will use these estimates as input values. The researchers acknowledge that while this will uncouple the work from any set timeline, as penetration predictions improve in the coming years, this work will be easily matched to any likely timeline of adoption.

3.3 Household AV Adoption

Household AV ownership is established based on the overall market penetration of AV technology as defined in Section 3.2. To avoid the assumption that all households are equally likely to purchase an AV, we utilize survey data to define different adoption patterns based on household income level.

An online survey was developed and administered in the fall of 2017 targeting commuters of Dallas-Fort Worth-Arlington Metropolitan Area. The survey distribution was achieved through mailing lists held by multiple entities (local transportation planning organizations, universities, private transportation sector companies, non-profit organizations, and social media), reaching a final clean sample of 1,607 respondents. One of the survey questions asked about an individual's willingness to purchase an AV under different cost scenarios, as shown in Table 8. Answers to this question are used to compute ratios of likelihood of purchasing an AV between individuals (and households) of different income levels under two different AV cost scenarios: (1) if AVs were at least $5,000 (five thousand) dollars more expensive than a regular vehicles (t0), and (2) if AVs were exactly the same price as a regular vehicles (t1).

Table 8 Survey question and sample distribution of answers

Imagine that you are planning to buy a car and self-driving cars are an available option. Consider also that ride-sourcing services already operate with self-driving cars. Which of the following options would you choose?		
Alternative	*raw %*	*cumulative %*
I would buy a regular vehicle (that is not self-driving). I still want to drive myself.	39.0	39.0
I would buy a self-driving car only if it was exactly the same price as a regular vehicle (that is not self-driving).	26.0	65.0
I would buy a self-driving car only if it was no more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	24.4	89.4
I would buy a self-driving car even if it were more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	7.6	97.0
I would not buy a car and I would rely on the use of ride-sourcing services (that operate with self-driving cars).	3.0	100.00

The adoption rates observed in the survey correspond to individuals' current perceptions (that are highly sensitive to the current technology developmental stage and associated safety) and, therefore, are not suitable for directly predicting AV adoption in future scenarios. However, these data can still be used to capture individuals' sensitivity to AV technology cost for each household income segment.

A simple binary logit model was developed, in which the adoption of AVs (in this case, accepting to buy AVs even if they were more than $5.000) was explained by individuals' household income, using the lowest income category as the base. The estimated results were then used in tandem with the number of households in each income segment in each of the Traffic Simulation Zones (TSZs) to find out the overall AV adoption. Finally, the logit model's constant was manually calibrated to reach the pre-defined overall AV adoption.

3.4 Trip Generation

The NCTCOG model performs trip generation in two steps: home based trips followed by non-home based trips. This section describes the proposed methodological changes for all production and attraction models.

Table 9 presents the 14 different trip types considered by the NCTCOG model, which are generated using the market segmentations shown in Table 10.

Figure 3 illustrates the proposed workflow for trip generation, which maintains NCTCOG's existing trip types and their segmentations while incorporating trips by households with AVs as per the previous model, and introducing a new segment to account for trips induced by ride-hailing.

The current NCTCOG model only generates the regular trips for non-AV households and uses the segmentations presented in Table 10. The changes proposed include generating trips induced trips due to the existence of new mobility services (such as ride-hailing) and all trips generated by AV households.

Table 9 Trip types

Name	**Trip Type**
HBW	Home based – work trips
HBSHOP	Home based – shopping trips
HBEDUK12	Home based – education trips – K-12
HBEDUCOL	Home based – education trips – College
HBSRE	Home based – social and recreational trips
HBPBO	Home based – personal, business, other trips
NHWRK_WRK	Non-home based – work/work trips
NHWRK_ESH	Non-home based – work/education trips, work/shopping trips, work/social-recreational trips
NHWRK_OTH	Non-home based – work/other trips
NHSHP_SHP	Non-home based – shopping/shopping trips
NHSHP_OTH	Non-home based – shopping/other trips
NHOTH_OTH	Non-home based – other/other trips
NHB_UNK	Non-home based – unknown trips
NHEDU	Non-home based – education trips

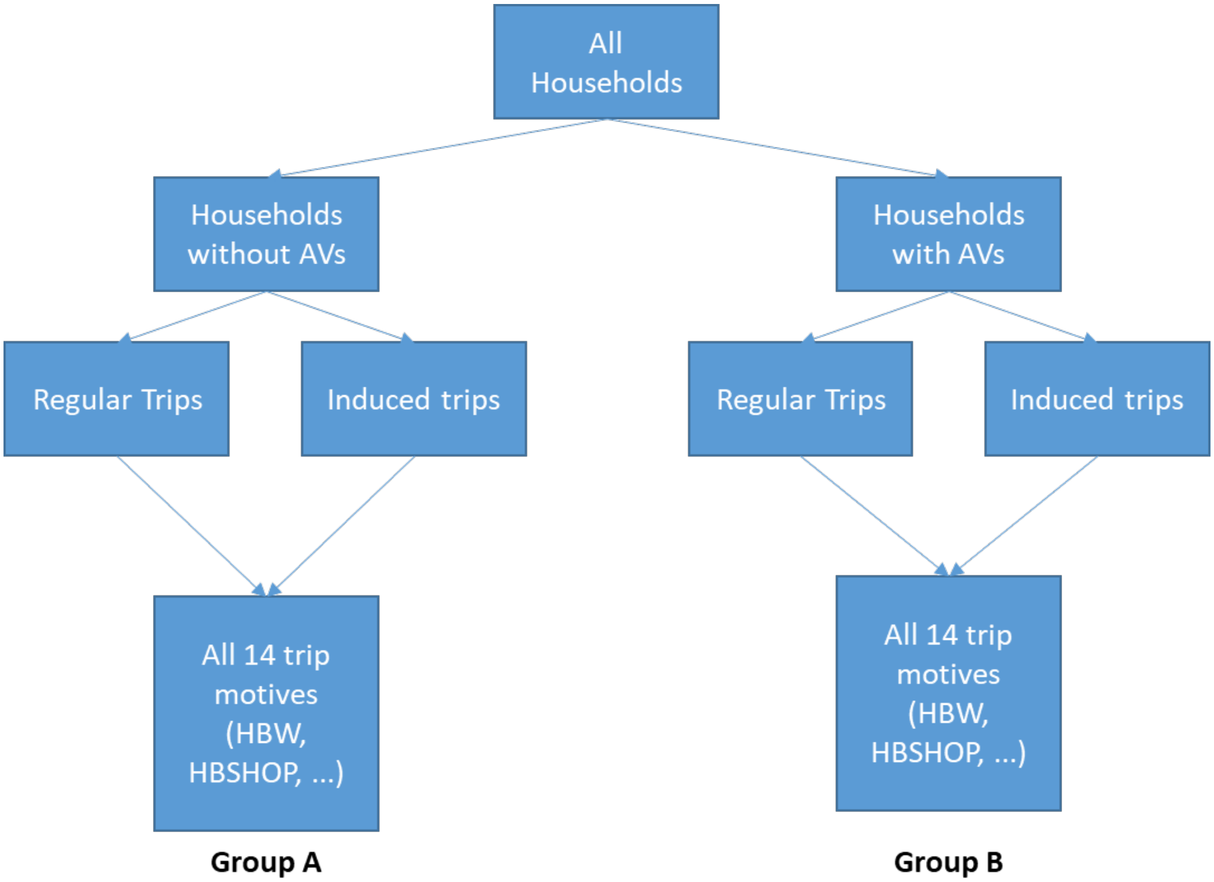

Figure 3 Diagram for trip generation

Table 10 Market segmentation for Trip Generation

Trip Purpose	Market Segmentation	
	Trip Production	Trip Attraction
HBW	Income × wrkcnt × vehcnt	Income×Industry
HBSHOP	Income × wrkcnt × hhsize	Income×Industry
HBEDUK12	numchild	Special Process by School District
HBEDUCOL	Income × wrkcnt	Num. of College/ University Students
HBSRE and HBPBO	Income × numchild	Income×Industry
NHWRK_WRK, NHWRK_ESH and NHWRK_OTH, NHSHP_SHP, NHSHP_OTH	wrkcnt	Income×Industry
NHOTH_OTH	numchild	Income×Industry
NHB_UNK	numchild	Proportional to all other NHB trips
NHEDU	A fixed rate per HH from Survey	School Type

The induced trips (for both non-AV and AV households) are created by applying a simple factor to the regular trips they produce. This is, in essence a point of exogenous variability. For instance, if there is reason to believe that the induced demand due to ride-hailing is about 2%, the regular trip tables from AV households and non-AV households are multiplied by 0.02 to generate their induced trip tables. The survey conducted in the Dallas-Fort Worth-Arlington Metropolitan region (mentioned in Section 3.3) revealed that approximately 6% of ride-hailing trips are induced trips. Furthermore, according to the 2017 National Household Travel Survey, approximately 0.4% of all trips Dallas-Fort Worth-Arlington Metropolitan region are made by taxis and ride-hailing services. The amount of induced ride-hailing trips can be obtained by combining these two figures: the additional induced ride-hailing trips represent 0.02% of all trips.

Once the trips for all groups have been generated, induced and regular trips are combined to form the total trips generated by households without AVs (Group A) and by households with AVs (Group B). In the mode choice stage, as explained in further detail in Section 3.6, the modes involving a personal vehicle (such as Drive Alone and Carpool) will be substituted by AV versions (such as Drive Alone – AV and Carpool – AV) for Group B. Its counterpart Group A will be subject to the regular mode choice, where AVs are not an eligible mode.

3.5 Trip Distribution

The current NCTCOG model uses the gravity model for trip distribution. Similarly to the trip generation stage, trip distribution is performed separately for home-based and non-home based trips. The changes presented in this section are applicable to both trip types.

Table 11 presents the segmentation used by the current NCTCOG model to distribute the trips generated in the previous step.

Table 11 Market segmentation for Trip Distribution

Trip Purpose	Segmentation for Trip Distribution
HBW	Income×Time Period (PK/OP)
HBSHOP	Income
HBEDUK12	Elementary, Middle and High School
HBEDUCOL	N/A (no further segmentation)
HBSRE and HBPBO	Income
NHWRK_WRK, NHWRK_ESH and NHWRK_OTH, NHSHP_SHP, NHSHP_OTH	N/A (no further segmentation)
NHOTH_OTH	
NHB_UNK	
NHEDU	

The trip distribution model used in this stage is based on travel times between OD pairs. The main modification proposed here is to modify the already-calibrated impedance functions to reduce individual's sensitivity to travel time, which would only apply to Group B in Figure 3.

3.6 Mode Choice

In this section we propose changes to the current NCTCOG model to include ride-hailing as a separate mode and consider the increased convenience of travel modes that use AVs.

The current NCTCOG model uses separate mode choice models for different activity purposes and different market segments. The market segments are based on income level and number of vehicles owned by the household relative to number of workers in the household. The mode choices available are drive alone, shared rides, walk to bus, walk to rail, walk to premium bus, drive to bus, drive to rail and drive to premium bus.

3.6.1 Addition of Ride-hailing

Since we expect ride-hailing to have a significant market share in the future, ride-hailing will be added to the mode choice set.

The utility function of this mode would include in-vehicle travel time, waiting time and travel cost, as well as an alternate-specific constant. The coefficients for some of these variables (i.e. cost, travel time and waiting time) will be the same as those used in the other models: the in-vehicle travel times for ride-hailing are considered to be the same as that for drive alone. The skim for cost of ride-haling will be generated as a function of the travel time and travel distance skims. The wait times for ride hailing can be made a function of the population density.

When generating multiple scenarios, the cost function, waiting time skims and overall attractiveness of ride-hailing trips can be altered based on the assumptions of overall usage of 9ride-hailing.

3.6.2 Modifications to Incorporate AVs in Households' Choice Sets

Following the structure so far, households have been split into two categories: those without AVs and those with AVs. The mode choice models proposed here differentiate between these two types of households as well. In essence, the modifications include the consideration that AVs will affect the following aspects of the trip:

- **Value of in-vehicle travel time**: Travel time in AVs would be less onerous than travel time in regular vehicles because passengers of AVs can be more relaxed and engage in other activities.
- **No driver's license needed**: Since AVs do not require drivers, individuals without license (children, differently abled individual) can also make use of AVs
- **Last mile connectivity**: AVs can be summoned for last mile connectivity from other modes

We propose the addition of market segments for households that own AVs. Since a single AV could possibly serve the needs of multiple members in a household, there need not be distinct market segments for households owning different number of AVs. The final market segmentation for the mode choice step is as shown in Figure 4.

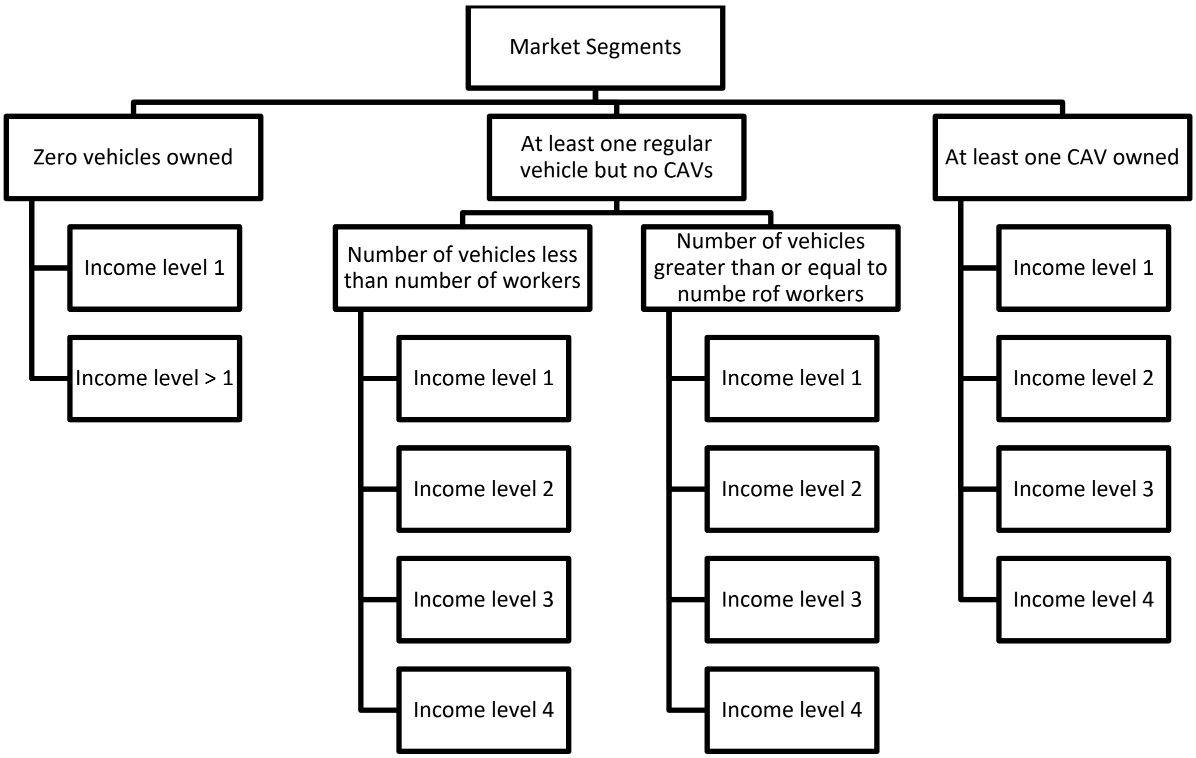

Figure 4 Market segmentation for mode choice

In households with AVs, all mode choices that require the use of household vehicles, namely drive alone, drive to bus, drive to premium bus, drive to rail, shared ride with 2 individuals and shared ride with at least 3 individuals is assumed to be carried out using AVs. To model the greater convenience of using AVs, the mode choice model for individuals from households owning at least one AV is prepared by modifying the mode choice model for trips generated in households with number of vehicles greater than or equal to number of workers as described below

In a general sense, the baseline constant for a mode captures the propensity of a person to use the mode due to unexplained factors. These coefficients can be adjusted to increase the mode share of AV based alternatives.

Modifications for lowering IVTT cost

In-vehicle travel time (IVTT) in AVs is less onerous than in-vehicle time in regular vehicles. We use data from a recent survey conducted in Dallas to estimate the difference of value of IVTT for drive-alone mode between households that own AVs and households that do not own AVs. In the mode choice model, if the coefficient of IVTT for a mode m is β_{IVTTm} and the coefficient for cost is (considered the same for all modes) β_{cost}, the value of IVTT in that mode is,

$$c_{IVTTm} = \frac{\beta_{IVTTm}}{\beta_{cost}}$$

Households that own an AV and households that have more vehicles than number of workers are assumed to have the same β_{cost} if both the households have the same income level. So, β_{IVTTDA} for households with AVs is computed as,

$$\beta_{IVTTDA}^{AVHH} = \beta_{IVTTDA}^{NAVHH} \times (1 - \Delta c_{IVTTDA})$$

where, β_{IVTTDA}^{AVHH} is the coefficient for IVTT of drive alone for households that own AVs, β_{IVTTDA}^{NAVHH} is the coefficient for IVTT of drive alone for households that do not own AVs and Δc_{IVTTDA} is the difference of value of IVTT estimated in the survey.

The correction for coefficients associated with IVTT has to be made for the modes drive alone, shared ride with 2 individuals and shared ride with at least 3 individuals. For the modes, drive to bus, drive to premium bus, and drive to rail, the correction should be applied only to the coefficient for IVTT inside the household vehicle and not the other mode.

<u>Possible improvements</u>

In this section, we outline some possible considerations that could further improve the proposed mode choice modeling strategy. Currently, these have not been incorporated into the proposed changes.

- Address potential increased parking convenience when using AVs
- Consider the change in the utility of the mode associated with transit vehicles if they are themselves, AVs.
- Account for the increased cost and delays when multiple people in the household use the same AV
- Given that drivers are not required in AVs, home-based education (K-12) trips will likely see an increase in the use of certain modes, namely drive alone.
- The modes drive to bus, drive to premium bus and drive to rail will likely be more attractive for households with AVs given the ease with which AVs can drop individuals at the bus or rail terminal and return home.

3.7 Production/Attraction to Origin/Destination

The section of the model that transforms productions and attractions into origins and destinations (PA2OD) will remain intact. The procedure originally used will be copied for both Groups A and B (Figure 3).

3.8 Time-of-day Split

The current NCTCOG model splits the 24 hour origin and destination (OD) trip matrices into four different time-specific OD matrices: morning peak (AMPK), evening peak (PMPK) and off-peak (OPK).

The same procedure from the current NCTCOG model will be utilized for Groups A and B.

3.9 Trip Assignment

In this section we detail the changes proposed to the trip assignment stage. The fundamental change proposed is to model the impact of AVs by varying how much road capacity each AV consumes while on a trip (instead of by changing the actual capacities of network links). This approach is expected to perform better for scenarios where the AV market penetration is not 100%, since it can reflect the actual number of AVs on specific road segments, which in turn depends on the travel patterns of households that own such vehicles.

3.9.1 The Passenger Car Equivalent (PCE)

The proposed approach assumes that, given a road where all vehicles are moving at the same speed, the total throughput for any given traffic volume depends on the proportion of AVs on the traffic stream. The latter is a result of the potentially smaller distance headways maintained by AVs when compared to manually driven vehicles. In planning models the maximum throughput is typically given by a fixed capacity value. However, given that the fraction of AV in any given segments is not known a priori, a network-wide change in link capacities may overestimate the performance of the system for low and medium levels of AV market penetration. In this context, we propose to maintain capacities as estimated in the original planning model, and to use the concept of passenger car equivalent (PCE) to capture the impact of the smaller headways enabled through automation. If we assume that the PCE of a regular manually driven vehicle is 1, the PCE of an AV represents the ratio of road capacity consumed by an AV to the capacity consumed by a regular vehicle traveling at the same speed. The PCE of a vehicle of type x is computed as follows:

$$\rho_x = \frac{l_x + D_x}{l_s + D_s}$$

where, ρ_x is the PCE of a vehicle of type x, l_x is the length of a vehicle of type x, l_s is the length of a standard vehicle which consumes a capacity of 1 PCE, D_x is the headway maintained by a vehicle of type x and D_s is the headway maintained by a vehicle having PCE of 1.

At this stage we consider 2 different cases of AV technology implementation. In Case 1, AVs rely solely on their onboard sensors to detect the position of other vehicles and obstacles in its surroundings. In Case 2, AVs are able to communicate with each other (CAVs) in addition to being equipped with sensors to detect their surroundings. We assume that humans do not actively vary their time headway based on speed of the leading vehicle (Tientrakool et al., 2011). In both cases, the time headway of human driven vehicles is kept constant at 1.1 seconds which is the mean of time headways maintained by human drivers according to a study by Sayer et al. (1997).

$$D_m = Vt_m$$

where, D_m: distance headway of regular vehicle, V: speed, t_m: reaction time of humans. The headways and resulting traffic flows of AVs and CAVs is explained below.

<u>Case 1: Autonomous vehicles cannot communicate with each other</u>

It is assumed that an autonomous vehicle would continuously determine the speed of its leading vehicle and its distance headway. Based on these parameters, the AV ensures that there is always sufficient headway for it to come to a complete stop behind the leading vehicle in the worst-case scenario that the leading vehicle decelerates to its maximum possible extent. To ensure this safe following distance, the headway left by the AV would be the sum of distance that would be covered by the AV in the time it requires to sense and react to movements by the leading vehicle (reaction time of AV) and the maximum possible difference in stopping distance between the two vehicles.

$$D_a = Vt_s + \frac{V^2}{2a} - \frac{V^2}{2a_{max}}$$

where, $D_a$is distance headway of AVs, $V$is speed, $t_a$is maximum reaction time of sensing system of AVs, a is preferred deceleration of AV, d_{max} is maximum possible acceleration of vehicle in front. Then the passenger car equivalent (PCE) of an AV would be,

$$\rho_{AV} = \frac{l_{AV} + D_a}{l_s + D_m}$$

where, ρ_{AV} is the passenger car equivalent of the AV, l_{AV} is the length of an AV and l_s is the length of a standard vehicle which consumes a capacity of 1 PCE.

<u>Case 2: Autonomous vehicles can communicate with each other</u>

The main difference between Case 1 and Case 2 is that in 2, the headway maintained by a CAV would differ based on whether the vehicle in front of it is a CAV or not. If the vehicle in front of it is a regular vehicle, the headway maintained by a CAV would be the same as that maintained by an AV in scenario 1.

$$D_{cm} = D_a = Vt_s + \frac{V^2}{2a} - \frac{V^2}{2a_{max}}$$

where, D_{cm} is the distance headway maintained by a CAV when following a vehicle that cannot communicate.

However, if a CAV is following another CAV, it can afford to maintain a much lower headway because acceleration rates may be coordinated via inter-vehicle communication. In the case of multiple CAVs following one after the other (CAV platooning), all platooned vehicles can agree on a common deceleration rate. The stopping distance of all CAVs in the platoon will be exactly the same (within a small tolerance). In this context the CAV would only need to leave a headway distance sufficient to compensate for the time it requires to communicate with the vehicle in front.

$$D_{cc} = Vt_c$$

where, D_{cc} is distance headway maintained by CAV when following another CAV, $V$is speed, $t_c$is maximum time required for CAV to communicate with vehicle in front and react. The PCE of a CAV will be,

$$\rho_{CAV} = \frac{l_{CAV} + \overline{D}_c}{l_s + D_m}$$

$$\overline{D}_c = P_m D_{cm} + P_c D_{cc}$$

where, ρ_{CAV} is the passenger car equivalent of the CAV, l_{CAV} is the length of the CAV, $\overline{D}_c$ is the average headway maintained by a CAV, $P_m$is the probability of the CAV following a vehicle that cannot communicate and P_c is the probability of the CAV following another CAV. P_c can be considered as the market penetration of CAVs. Then,

$$P_m = 1 - P_c$$

Note that in scenario 1, ρ_{AV} is independent of the proportion of AVs on the road whereas ρ_{CAV} is dependent on the proportion of CAVs.

3.9.2 Sample Values

Using the parameter values that are shown in Table 12, sample values for ρ_{AV} and ρ_{CAV} for different values of speed (V) and market penetration of AVs/CAVs (P_c) are shown in Figure 5 and Figure 6. The ratio of vehicle flow with CAV/AVs to the vehicle flow with only regular vehicles is shown in Figure 7 and Figure 8 respectively.

Table 12 Parameters used to calculate sample PCE and flow ratios

Parameter	Value
d_{max}	8
d_{min}	5
d	Uniformly distributed between d_{max} and d_{min}
t_m	1.1
t_a	0.245
t_c	0.181
$l_s = l_{AV} = l_{CAV}$	4.8

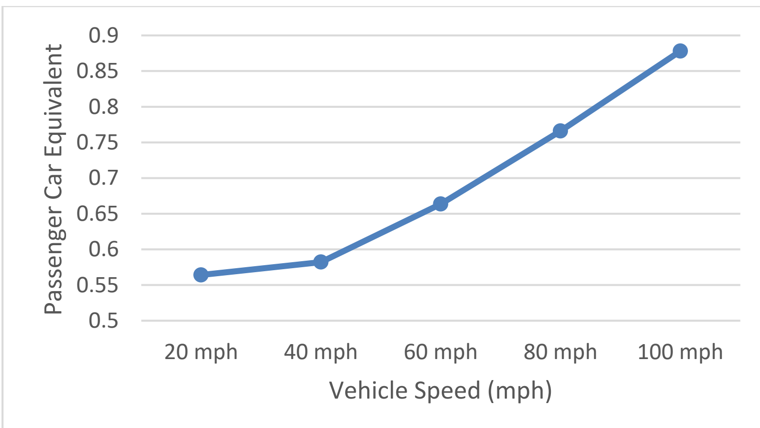

Figure 5 Passenger car equivalent of AVs vs speed

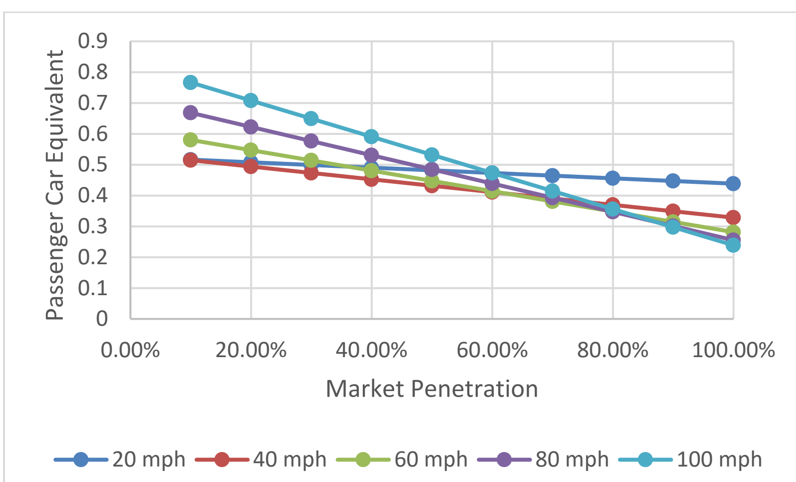

Figure 6 Passenger car equivalent of CAVs vs market penetration for different speeds

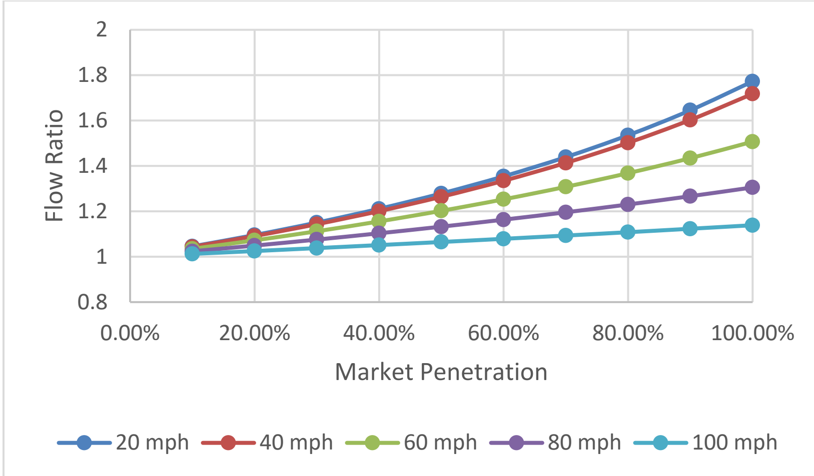

Figure 7 Ratio of flow of traffic with AVs to flow of traffic with only regular vehicles vs market penetration for different speeds

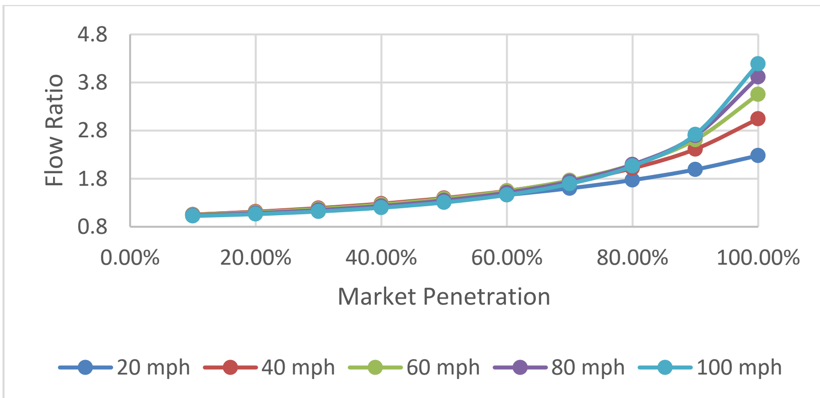

Figure 8 Ratio of flow of traffic with CAVs to flow of traffic with only regular vehicles vs market penetration for different speeds

3.9.3 Implementation

TransCAD provides the option to have different vehicle classes and assign different PCEs to each class. The current NCTCOG model has 3 classes of vehicles. A new class is to be added for AVs. To capture the difference in space utilization of AVs when compared to regular vehicles, we assign a different value of PCE for AVs. Figure 5 and Figure 6 show that PCE values which corrects for the difference in capacity utilization is dependent on the speed of vehicles and market penetration of AVs on the road. Since speed of vehicles and proportion of AVs on links are dynamic and difficult to be determined beforehand, to simplify the modeling task, we propose the use of a single PCE value that best represents the entire range of PCE values that would be observed in the network. If the proportion of AVs and speed of some links in the system can be known prior to the trip assignment procedure, the capacity of these links can be adjusted so that it exactly matches the expected capacity. For example, if we assume that there are managed technology lanes in the network where only AVs operate and a minimum speed is maintained, the capacity of these links can be changed.

3.9.4 Possible Improvements

In this section, we outline some possible improvements to the proposed traffic assignment modeling strategy that have not been incorporated into the current proposed changes.

- PCEs (in the traditional sense) are computed empirically from field data. The PCEs determined above may have to be further adjusted and validated using microscopic simulations.
- The improvement in traffic efficiency because of speed stabilizing and shockwave dampening effect of AVs is not considered.
- CAVs may actively try to group together and form platoons for more efficient traffic flow (the probability of a CAV to follow another CAV would be higher than the market penetration of CAVs). The above procedure only considers the grouping together of CAVs by chance.
- Mechanism can be added to capture the difference in capacity utilization of AVs at different speeds and market penetrations
- If AVs are used for transit, transit assignment steps also need to be changed.

3.10 Framework Summary

In this chapter we outlined a comprehensive methodology to extend the capabilities of an existing four-step planning model in order to consider the impacts of new transportation technologies and services. The proposed approach can endogenously model the impacts of such technologies on trip generation, distribution and ultimately on traffic performance, given a number of assumptions summarized in Table 7. Such assumptions are necessary to compensate for model limitations and/or due to insufficient data to explicitly model some aspects of the decision process. By combining different possible values for the exogenous factors we expect to generate multiple scenarios that can describe the range of potential impacts of CAVs.

Table 13 Main assumptions and exogenous parameters

Forecasting Phase	Assumptions
AV Adoption	Overall AV Ownership Distribution of AVs in households
Trip Generation	Trip production factor for households with AVs Induced trip production factor due to the availability of ride-hailing
Trip Distribution	Generalized cost for distribution function

Mode Choice	Ride Hailing
	    Overall attractiveness
	    Ride-hailing cost function
	    Ride-hailing availability (wait times)
	AV based modes
	    Overall attractiveness
	    Reduction factors of sensitivity towards in-vehicle travel time

Trip Assignment	PCE of CAVs

Chapter 4. Code Documentation

4.1 Introduction

This chapter describes the modifications made to the existing codes and new programs that were written to perform the simulations.

4.2 GISDK Code for Running Model in TransCAD

This section documents the changes made to the GISDK code provided by NCTCOG. In the rest of this section, we refer to the original code provided by NCTCOG as version 1 and the code produced after modification as version 2.

4.3 AVAllocation.rsc

This is a new module that has been added in version 2. This module classifies households as households that own AVs and households that do not. This module uses the household segmentation files as input, adds one more layer of segmentation based on AV ownership of households and writes this as output. In the current version, the segmentation of households based on AV ownership is purely determined by income. The proportion of households at each income level that own AVs is specified externally in the configuration file.

4.4 TripGen.rsc (Home based)

This module performs home based trip generation for households with and without AVs. The household segmentations (including segmentation based on AV ownership), trip production and attraction rates are used as input files. For non-homebased trips, the trip production and attraction rates used for trip generation is the same as those provided in the input files. In the case of households with AVs, for every trip purpose there is a “Trip Generation AV factor” that is read as input from the configuration file. The trip production rate for AV households will be the trip production rate of non-AV households multiplied by this trip generation factor. Trip attractions are also computed separately for households with different income and different AV ownership. After calculating trip productions and attractions independently, they are balanced so that the total trip generation is equal to total trip attraction.

For educational trips, version 1 did not compute trips produced and attracted at different school levels such as “Elementary”, “Middle school” and “High school” separately. However this classification would be required at the non-home based education trips generation stage. So total trips generated were disaggregated into these 3 levels in the proportion of the average number of years spend by students at these three school levels.

4.5 CVM.rsc

This module in version 2 is exactly the same as that in version 1.

4.6 InitializeACTRDWY.rsc

This module in version 2 is exactly the same as that in version 1.

4.7 RoadwaySkim.rsc

This module in version 2 is exactly the same as that in version 1.

4.8 HBTripDist.rsc

This module performs home based trip distribution. There is no change in the procedure used for distribution of trips of households without AVs between version 1 and version 2. For households with AVs, the effective impedance matrix used for trip distribution is scaled by the AV trip distribution factor that is read from the configuration file.

In version 1, trip distribution of home-based K12 trips is not done in this step. The production-attraction matrix for K12 trips is directly made available as an input. Since this production-attraction matrix is not segmented based on income, we were unable to classify home-based K-12 trips as AV trips or non-AV trips. As a temporary fix, we have assumed all K-12 trips to be non-AV trips.

4.9 NHBTripGen.rsc

In version 2, the procedure used for non-home based trip generation of households with AVs and households without AVs remains the same as the procedure used for non-home based trip generation in version 1. All changes in code were made to accommodate the extra household segments produced because of the classification based on AV ownership.

4.10 NHBTripDist.rsc

This module performs non-home based trip distribution. This module uses the same AV trip distribution factor used in the module for home based trip distribution to adjust the impedance experienced by individuals from households that own AVs. This module also splits the home-based and non-home based trip distribution matrices into trip distribution matrices specific to the household segments used by the mode choice model.

4.11 TransitPrep.rsc

This module in version 2 is exactly the same as that in version 1.

4.12 TransitSkim.rsc

This module in version 2 is exactly the same as that in version 1.

4.13 ModeChoice.rsc

This module performs the mode choice for different household segments. Changes were made to this module to accommodate household segmentation based on AV ownership. The mode choice is performed based on the mode choice model (.mdl) files provided as input. These model files were changed externally to accommodate ride hailing and different characteristics for drive alone and shared ride options for households that own AVs.

4.14 PA2OD.rsc

This module performs the PA2OD conversion for the PA trip matrices of each mode. Time of day factors are used as input in the PA2OD conversion. The same time of day factors is used irrespective of whether the trip is made by an AV or a non-AV. For ride-hailing trips, all OD trips are reduced by a factor of the average occupancy (not including the driver) in these vehicles. This factor is read from the configuration file.

4.15 RoadwayAssignment.rsc

This module performs the traffic assignment of non-transit OD trips created at the PA2OD stage. The relative gap required for convergence in the last feedback loop was changed from 0.0001 to 0.001 for faster convergence. The effective passenger car equivalent of AVs is read as input from the configuration file. The modes, AV and SAV (equivalent to DA and SR in households without AVs) use the PCE for AVs. The vehicles used for ride hailing is considered as AVs if the parameter "AV Ride Hailing" is set to 1 in the configuration file, in which case the PCE of AVs will be set for ride hailing as well. Otherwise, the PCE of ride-hailing will remain 1.

4.16 TransitAssignment.rsc

This module performs the traffic assignment of transit OD trips created at the PA2OD stage. Modifications were made to this module, to accommodate the new household segments generated based on AV ownership. Transit assignment for households with AVs and without AVs is done in the same way.

4.16.1 ModeChoiceModeler.py

ModeChoiceModeler.py is a python script used to produce the mode choice model files (.mdl) that is to be used as input in the mode choice step of version 2 of the NCTCOG model. It takes in as input the mode choice model files in version 1 and based on input parameters read in the configuration file, outputs the mode choice model files that is to be used with version 2. All configuration variables are located in the configuration section of the script (line 4 to line 34). The input folder, output folder, ride hailing service characteristics and change in value of time for AV users is set in the configuration section.

Chapter 5. Modeling Results

In this chapter, we outline the simulation results of three scenarios using the updated NCTCOG model. The demographics and networks used during this stage correspond to that of 2014.

The main objective of these three scenarios was two-fold:

- To verify that the model yielded reasonable results;
- To have a first glimpse of understanding what the initial effects of AVs will be.

The summary of the main inputs used in the three scenarios can be found in Table 14.

Table 14 Main input parameters for scenarios

Parameter	Scenario 1	Scenario 2	Scenario 3
Overall AV Ownership Rate	0.00	0.20	0.30
AV Trip Generation Inflation Factor	NA	1.05	1.05
Mobility Inflation Factor	1.00	1.01	1.01
AV VOT Factor	NA	0.75	0.75
AV Passenger Car Equivalent	NA	0.70	0.70
Ride-Hailing Cost/Min	0.49	0.49	0.49
Ride-Hailing Occupancy	1.10	1.10	1.10
Ride-Hailing uses AVs	No	No	No

The main household and employment demographics, common to all three scenarios, are listed in Table 15.

Table 15 Household and employment demographics

Population - Total	6,894,870
Households - Total	2,477,569
Household Income < 35k	710,032
35k < Household Income < 50k	323,195
50k < Household Income < 75k	446,265
75k < Household Income	998,077
Employment - Total	4,302,808
Employment - Basic	1,038,815
Employment - Retail	411,492
Employment - Service	2,852,501

The main results from the trip generation can be found in Table 16, which show a consistent growth in number of trips as was expected given Scenario 2 and 3's increased trip production rates. Curiously, HNW trips seem to have absorbed most of the extra trips. It should be noted that, for the current implementation, NHB trips were not subject to the increased trip rates, making their totals constant throughout all three scenarios.

Table 16 Summary of trip generation results – Number of trips during AM peak

Trip Type	Scenario 1	Scenario 2			Scenario 3		
	Non-AV HHs	Non-AV HHs	AV HHs	All HHs	Non-AV HHs	AV HHs	Total
HBW	3,831,243	3,005,439	864,117	3,869,555	2,589,784	1,279,771	3,869,555
HNW	9,865,583	7,954,905	2,112,901	10,067,806	6,953,101	3,166,365	10,119,466
NHB	911,077	729,836	181,242	911,077	639,007	272,070	911,077
Total	14,607,903	11,690,180	3,158,260	14,848,438	10,181,892	4,718,206	14,900,098

A summary of the trip distribution can be found in Table 17. As expected, AV households seem to be engaging in longer trips than their non-AV counterparts.

Table 17 Summary of trip distribution results – Average trip length (minutes)

Trip Type	Scenario 1	Scenario 2		Scenario 3	
	Non-AV HHs	Non-AV HHs	AV HHs	Non-AV HHs	AV HHs
HBW	28.24	27.43	28.81	27.04	28.40
HNW	15.10	14.88	15.88	14.75	15.75
NHB	15.86	15.76	15.85	15.72	15.78
Total	18.59	18.16	19.42	18.01	18.97

The main results from the mode choice stage can be seen in Table 18. Ride-hailing services comprise approximately 4% of all trips. This is considerably higher than what is observed in reality (less than 1% of all trips), most likely due to the service being widely available throughout the whole modeled area with the same level of service.

Table 18 also shows that the number of AV trips seems to roughly follow the AV penetration rates of scenarios 2 and 3 (20% and 30%, respectively). As the penetration rates increase, we can see a significant drop in the transit shares. Given transit already small has a considerably small number of trips to begin with, the approximately 30,000 transit trips "lost" are quite significant.

Table 18 Summary of mode choice results – Number of trips and mode shares during AM peak

Mode	Scenario 1		Scenario 2		Scenario 3	
	Trips	Share	Trips	Share	Trips	Share
AV	-	0.00%	3,833,440	18.68%	5,725,616	27.81%
Non-AV	19,147,733	94.81%	15,632,927	76.20%	13,828,184	67.16%
Ride-Hailing	857,904	4.25%	877,235	4.28%	872,594	4.24%
Transit	190,952	0.95%	172,938	0.84%	162,873	0.79%
Total	20,196,590	100.00%	20,516,540	100.00%	20,589,267	100.00%

The main assignment results are summarized in Table 19 and Table 20. As penetration rates increase, Table 19 illustrates that total VMT go up while the VHT stay fairly undisturbed. This is likely due to the AV efficiency gains in the network.

Table 19 Assignment results - VMT and VHT

Mode	Scenario 1		Scenario 2		Scenario 3	
	VMT	VHT	VMT	VHT	VMT	VHT
Non-AV	187,562,388	5,363,363	156,309,168	4,325,250	140,498,142	3,815,996
AV	--	--	35,518,603	1,052,285	52,948,020	1,548,822
Ride-hailing	2,935,936	97,938	2,986,247	98,553	2,975,708	97,324
Trucks	16,157,948	340,892	16,196,312	338,350	16,219,713	337,049
Total	206,671,594	5,802,658	211,010,330	5,814,438	212,641,582	5,799,191

The average trip lengths, as seen in Table 20, seem to follow most expectations: AVs engage in longer trips (in terms of travel time) than their non-AV counterparts. In terms of distance, however, there seems to be little difference between the two modes.

Table 20 Assignment results - Average trip lengths

Mode	Scenario 1			Scenario 2			Scenario 3		
	Veh. Trips (x100,000)	Avg Dist. (mi)	Avg. Length (min)	Veh. Trips (x100,000)	Avg Dist. (mi)	Avg. Length (min)	Veh. Trips (x100,000)	Avg Dist. (mi)	Avg. Length (min)
Non-AV	198.40	9.45	16.22	163.28	9.57	15.89	145.23	9.67	15.77
AV	--	--	--	38.33	9.27	16.47	57.25	9.25	16.23
Ride-hailing	7.80	3.76	7.54	7.97	3.74	7.42	7.93	3.75	7.36
Trucks	5.67	28.49	36.07	5.67	28.56	35.80	5.67	28.60	35.66
Total	211.89	9.75	16.43	215.25	9.80	16.21	216.09	9.84	16.10

Chapter 6. Conclusions

In this document, we presented recent trends in the literature regarding how transportation agencies can deal with modeling AVs and ride-hailing services, as well as several authors' predictions regarding AV technology's penetration rates.

We also outlined a clear framework for incorporating AV trips and ride-hailing trips into NCTCOG's current TransCAD model, along with supporting documentation of the code.

Finally, we presented the results from three simulation scenarios, all of which yielded reasonably sound results that conformed with the changes made to the model (e.g. lower sensitivity to travel time lead to longer trips).

The next steps in this effort can involve two main fronts:

- Developing further improvements to the model, such as: considering the repositioning trips performed by ride-hailing vehicles as well as the empty trips for AVs; modifying the "ride+transit" modes such that they more accurately reflect AVs ease of picking up and dropping off passengers at transit stations
- Running further scenarios with different inputs, such as: demographics, networks, penetration rates.

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