ABSTRACT

Title of thesis: SCENARIOS ANALYSIS OF AUTONOMOUS VEHICLES DEPLOYMENT WITH DIFFERENT MARKET PENETRATION RATE

Hang Yang, Master of Science, 2017

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Autonomous vehicles(AVs) play a lead role in the future of transportation. They provide a safe travel mode by eliminating human driving error. The reduced reaction time lag associated with AVs will bring significantly more capacity to the current traffic network and help people travel more efficiently and comfortably. AVs also liberate drivers' hands, creating more opportunities for drivers to make use of travel time. With the rapid development of machine-learning technology, it is predicted that autonomous vehicles will appear in the automobile market within two decades. This thesis integrates AVs into an existing four-step transportation model by modifying the model parameters and conducting an impact analysis on what autonomous vehicles bring to the model. Since originally there is no AV component in the model, this thesis has applied a feasible way to integrate AV behavior into the model and develop five different future scenarios to see the possible impact.

SCENARIOS ANALYSIS OF AUTONOMOUS VEHICLES DEPLOYMENT WITH DIFFERENT MARKET PENETRATION RATE

by

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Chapter 1: Introduction

Background

Autonomous vehicles (AVs) are first mentioned in the early 1920s, conceived as remote-control automobiles. Over the next 50 years, AV development was very slow, as pre-directing control had stalled. In 1980, the development of AVs began speeding up; over the next 20 years, industries and academics began using vision control. Today, with the development of computers, sensors and control algorithm, AVs are becoming more realistic for use by the general public. From as early as the DARPA Grand Challenge in 2007 to today, technology companies such as Tesla, Uber and Google announced their own autonomous vehicles, predicting that even though we may not have seen AVs on the road yet, we can expect them within two decades. Therefore, we need to foresee AVs possible benefits for the general public and their influence on the traffic network.

AVs could help people travel more safely and comfortably. Due to their pre-programmed driving behavior, they are able to eliminate human factors, such as driving while drinking, which may cause accidents. In addition, computers could make better decisions to avoid obstacles and, after detecting a possible collision, decelerate earlier than human drivers. Armed with a better reaction time than humans and amounted sensors, AVs are able to detect and handle more serious situations and sometimes, may be able to avoid dangers that humans could not predict. People may also have incentives to own an autonomous vehicle because it drives better than the typical human driver; AVs will accelerate and decelerate smoother because the short reaction time allows them more time to accelerate or decelerate.

Besides the improvements of safety and comfort, AVs also give the driver a chance to liberate their hands. This will allow drivers/passengers to get more value from in-vehicle travel drive time by allowing them to switch their attention from driving to other activities, such as using a cellphone, taking a nap, enjoying entertainment or working. Because of this benefit, the utility of choosing AVs to travel will increase and that will make this travel mode more attractive. The travel distance and number of trips will also benefit from the increased utility of AVs. Passengers are more likely to take additional trips—trips that they originally did not have time to take—if they could use this in-vehicle travel time to get other things done.

Although AVs will likely bring more trips to the traffic network, they may still help reduce the congestion on the road. Benefiting from their computers and sensors, AVs can operate with a lower the reaction time, thus allowing a shorter distance with others on the road. AVs may also reduce the influence of shock wave due to their smooth acceleration and deceleration.

Motivation

With all these distinguishing benefits, AVs will certainly be a dominant personal travel choice in the future. However, the data of AVs are rare so that we do not know how they really affect the traffic network. Very little work has been conducted in this field. Recent research published by the Transportation Research Board in 2016 (Lavasani, Jin and Du) presents an AV market penetration model to estimate the AV adoption rate in future years based on previous technology adoption experience. This model predicts that we shall see AVs on the road within 20 years and they will penetrate the market heavily within 30 years. In addition, several cities in the U.S. and around the world have issued permission for AVs to test drive. The U.S. federal government also issued an AV policy, including their regulation and guidance. Therefore, to evaluate those AV passengers' behaviors, the AV impact to the traffic network is needed in a long-term planning model.

AVs are not like today's typical vehicles in that they have certain characteristics, like auto-driving, that will not appear in the current traffic model. Those different characteristics will result in changes in the model parameters. The travel demand may very likely increase due to several benefits that come with AVs. First, the in-vehicle travel time cost reduction will increase the utility of choosing AVs; travelers are likely shift their travel mode to AVs if they could. Since AVs may have ability to auto-park, travelers' parking costs may lessen. Also, the government may pass legislation to allow AVs the use of traffic facilities, such as the toll lanes, for free. The above three benefits will result in travel demands that increase traffic congestion. However, due to the shorter car-following distance and better driving performance, AVs may help decrease traffic congestion, even though the travel demand increases. Those characteristics will need to be modeled thoroughly in the planning model to accurately capture their impact.

A four-step planning model is still a popular transportation model worldwide, although some more advanced models, such as agent based model (ABM), have been established. The traditional four-step model has some inevitable disadvantages that will essentially miss some characteristics of AVs. It is not a dynamic model, so researchers are not able to repeat the re-routing functionality of AVs. It also models on trips based on a gravity model but not individual characteristics, so it will not achieve any individual results; this eliminates the ability of imitating AV's car sharing ability. Despite these disadvantages, many agencies and governments are still working with a four-step model.

This thesis models the AV's behavior in an existing four-step model of the Maryland region, the Maryland Statewide Transportation Model (MSTM). The objective is to integrate the AV as a new travel mode in the model and assess the impact that AVs bring to the entire network system. Beyond that, this thesis also seeks to approach the objective with an easier but reasonable way. Currently, this four-step model doesn't have an AV mode in the mode choice part. It is generally in prior preparation to integrate AV travel mode into this model before we do any further impact analysis. However, it is a massive effort to integrate one mode into a four-step model, especially a large regional model like MSTM. To avoid time-consuming work and to make this approach benefit other regions, this thesis introduces a simpler way to address this issue.

AVs are likely to be on the road within 20 to 30 years. However, what the future of this region may look like is unknown. In order to better assess the impact of AVs, this thesis introduces four different future scenarios. This method shows us the overall impact of AVs to the network and differences between different scenarios.

Problem Statements

This thesis answers the designed questions listed below:

1. How can researchers integrate AVs into the current four-step model without changing the model structure? The current four-step model includes trip generation, trip distribution, mode choice and traffic assignment. As a new travel mode, AVs will not just affect those four steps but also the car ownership model; adopting this new mode requires the change of every code line and input file in the model. It is very important to address this problem for both simplicity and to make this method applicable for other regions.

2. How does travel mode, vehicle miles of travel (VMT) and traffic congestion change if AV's penetration rate changes? AVs will potentially increase utility for travelers. Their attractive features will increase travel demand. AVs may also decrease traffic congestion because of less following distance. Accurately modeling AV characteristics and predicting its impact will be important for future planning.
3. How do AVs influence different scenarios? Different future scenarios will give more references for policy making and infrastructure investment. They are important indicators and reflect the sensitivity of AVs to certain assumptions or infrastructure demands.

Contributions

This thesis introduces a way to integrate a new travel mode into the existing four-step model without changing model structure. This method is cost efficient in terms of time and could easily apply to any other four-step network with less coding ability. Due to the complexity of this four-step model, this thesis divides the integration of the AV mode into four steps. First, an external car ownership model has been considered to determine future year AV penetration. Second, two different trip generation models have been applied to AVs and regular vehicles separately. Third, two different mode choice models have been used to accommodate different characteristics of AVs and regular automotive. Fourth, trips from both AVs and regular automotive with mode choices are calculated and applied to the traffic assignment model. These steps will be described in detail below. After the model parameter modification, four different comprehensive scenarios will be considered as possible futures to conduct analysis.

AV penetration rate

In the original MSTM, there is no car ownership model. Instead, this model directly distributes generated trips into different travel modes with a logit model. Due to this limitation, the only way to add another vehicle type into this model is to pre-determine the AVs' penetration rate. To estimate the adoption rate, previous work done by Lavasani et al. (2016) has been considered as a reference. They predicted the AVs' adoption rate with a generalized bass diffusion model based on other technology adoption experiences.

Trip generation separation

MSTM uses census data for trip generation purposes. Since the AVs penetration rate has been pre-determined, the proportion of AV is applied into the model by dividing the census data correspondent to the AV portion and regular vehicle portion. Based on the possible increase of travel demand incurred by AV, the trip generation step will be modified for the AV portion to better reflect the characteristics of AV. In the most recent research, Long T. Truong et al. (2017) has estimated the trip generation impacts of AV by assuming that AV could fill the travel gap that people could not drive by themselves. However, this assumption has some limitations in that it did not consider the car's accessibility. This thesis will introduce a simple model to modify the additional trips by different income groups and trip purposes.

Mode choice

Two different sets of parameters are applied to two mode choice models. In those two models, the transit portion remains the same to ensure AVs owners and non-AVs owners have the same utility while choosing the transit as travel mode.

Traffic assignment

In this section, two sets of trip origin-destination(OD) tables, which include the travel mode choices, are combined into one trip OD table. The capacity will increase due to introducing AVs. Patel et al. (2016) have conducted work on how AV behavior will influence the network; they applied the classic green shield model in a simulation and obtained the capacity with different AV market penetration rate. This thesis takes that analysis as reference in capacity change and then conduct the assignment work.

Organization

The remaining part of this thesis is organized as follows: Chapter 2 discusses the literature review of relating papers to traffic models, AV characteristics and future planning. Chapter 3 introduces the current four-step model and the necessary modifications to integrate the AV behavior into the traffic model. Chapter 4 discusses the scenarios build. Chapter 5 presents the results of each scenario and analyze the AV's impact to different scenarios. The conclusion is discussed in Chapter 6.

Chapter 2: Literature Review

Introduction

This chapter will provide an overview of literature related to integrating AV behavior into the four-step model. Next section will illustrate the previous work related to AVs modeling as well as autonomous vehicles' behavior and impact prediction. The last section will discuss the previous work on modeling AV's characterization.

Autonomous Vehicles

Autonomous vehicles(AVs) have garnered a lot of attention in the last few years, although industries are still testing AVs. Recent research on AV modeling and impact predictions have became more and more mature. From the time when vehicles in the DARPA challenge were attempting to avoid obstacles until now, few states in the U.S. have issued permission for test driving of autonomous vehicles; but the potential benefits of AVs have pushed people to pay more attention. The U.S. is a country built on wheels; with over 261 million registered passenger cars (Hedges Company 2016), it is obvious that people in the U.S. like to have their own cars. Zhang et al. (2015) presented research that simulated the performance of shared autonomous vehicles (SAV) in an agent-based model with a dynamic ridesharing method. Their results indicate that SAVs could reduce trip delays, trip costs and vehicle miles traveled (VMT). Krueger et al. (2016) presented an SAV adoption model based on the stated choice survey in Australia. Their results show that SAVs may be more attractive to young travelers and that their acceptance is very sensitive to service attributes.

However, what those services will look like is very unclear to travelers, especially if they haven't even experienced AVs. Cools et al. (2017) proposed a logistic regression model to estimate the interest variables to SAVs from a stated adaptation experiment. They found that travelers are not very sensitive to those variables, which indicate that the current market is not paying attention to SAVs. Even though this study focused on estimating the market response of autonomous taxis in Belgium, people seemed to not like the idea of using SAVs, which may also occur in U.S. Besides, SAVs are more like a public transit system; it will need a large amount of initial investment from the government. The deployment for SAVs will definitely require more time than AVs. For simplicity purposes, this thesis will assume all the AVs are owned by individual travelers.

Autonomous vehicles model

Although a lot of research has addressed the objective of AVs, very few have been examined the integration of AVs into a traffic planning model. In 2015, Levin et al. first proposed to evaluate the influence of AV ownership on trip, mode and route choice in a classic four-step planning model in Austin, Texas. They made assumptions that AVs are going to appear in 20 to 30 years with increasing network capacity and self-parking ability. They divided car ownership by different value of time (VOT) and introduced a Boolean variable to determine whether this class uses AVs entirely or not at all. Though the issue of not achieving convergence in traffic assignment may occur with multi-class formulation, they are still able to produce reasonable results since this issue is common within all models that use multi-class VOT. However, one main challenge of integrating AVs into a current model is how to decide the penetration rate overall and by different groups of people. Levin's way of achieving that was to divide them into different income groups. The disadvantage of this is that not everyone in a high-income group will own an AV and conversely in a low-income group.

Kroger et al. (2016) introduced a traffic demand model for the U.S. and Germany to model the impact of AVs. This model has a similar procedure as a four-step model, except it only runs the first three steps. They apply an AV diffusion model as an external model in order to model different scenarios with different AV proportions. The core model uses NHTS data to conduct the trip generation and mode choice part together, followed by a trip distribution procedure. Their results showed that AVs both in Germany and U.S. will likely increase the VMT and the travelers' travel mode will likely shift from transit to cars. This research was conducted on AV impact analysis and a comparison between Germany and U.S. by using a very simplified four-step model. This trend will also become more distinct with the AV penetration rate increasing. It significantly reduced the computational work on calculating user equilibrium by ignoring the traffic assignment step. However, this makes them lose the ability to look into the potential impact of AVs in the traffic network.

Since the agent-based model (ABM) is now very popular in the transportation field, a few studies are also looking at the impact of AVs. Azevedo et al. (2016) proposed an extended ABM to simulate the AV system with three different time-scale simulation levels. They specifically simulated the AV system on short-term and mid-term levels to capture its impact on travel behavior. The main difference between a four-step model and ABM is that one is mainly served as a long-term planning model and the other one is a simulation-based model that mainly serves to see short-term or mid-term impact. The advantage of using ABM is that ABM can collect individual travel information, which allows researchers to do more individual-level research, such as average waiting time (Azevedo et al., 2016).

However, ABM has disadvantages compared to the traditional four-step model. First, it requires more computational time than the four-step model because of individual-level computation. Second, it is better to use it with the already existing travel mode since it requires more characteristics of each travel mode. AVs are still in the testing stage and their behaviors are mostly predictions. With more predicted inputs, the uncertainty of the results may become greater than the traditional four-step model. After all, the main goal of assessing AVs' impact is to see the approximation trends of how AV behavior changes will influence the traffic network. This thesis chose to integrate AVs' behavior in MSTM to better present the impact of AVs with fewer required resources.

Adoption rate of autonomous vehicles

Most researchers believe that AVs will appear in the market between 2020 to 2030, but it is uncertain when and how AVs will penetrate the market. In recent years, research has been done on the adoption trends of AVs.

Litman (2015) proposed an AV adoption rate based on previous vehicle technology deployment experience. He assumed that AV's deployment might follow the pattern of automatic transmission if without mandates, which took nearly five decades to reach market saturation. Lavasani et al. (2016) proposed a Bass diffusion model, which was also based on previous technologies adoption data. They used indicators, including innovation factor and imitation factor, to predict the AV market penetration. They also included some social economic data as external indicators to modify the base model into a generalized model. Along with those efforts, a sensitive analysis of market size and price ratio was conducted to better understand the possible impact of those two indicators on AV market penetration. Their results demonstrate that the market size has a dominant impact on AV market penetration, but the initial AV cost relative to conventional vehicles seems irrelevant compared with the market size. This conclusion is surprising, because generally, the cost of a product is one of the most important factors that will influence its attractiveness to buyers. Bansal et al. (2016) proposed a simulation-based framework to forecast long-term adoption levels of connected autonomous vehicles (CAV). They developed different scenarios based on different annual increments in Americans' willingness to pay (WTP) and annual drops in technology prices. They designed a survey to collect respondents' WTP for CAV technologies, their social demographics and social economics data. A Monte Carlo simulation-based model was proposed based upon those data. It used probabilities generated by estimating a multinomial logit (MNL) model in BIOGEME to assess the vehicle transaction and technology adoption choice of each respondent every year. Their results suggest that WTP, technology cost and government regulations all play important roles in the adoption of CAVs. The adoption rate varies from 24.8% to 87.2%, depending on different annual price drop and increased annual WTP.

Most research related to AV impact analysis uses different market penetration rates directly to build different scenarios to forecast impact under different situations.

Autonomous vehicles characterization

The previous section discussed AV modeling in various ways. This thesis is using MSTM, an existing four-step model for the Baltimore-Washington metropolitan area, to integrate AVs and analyze the potential impact that may occur in this region. However, the main challenge of integrating AVs is how to predict AVs' characteristics. Fortunately, there is substantial literature with already published results that are considered relevant to this thesis.

Impact on trip generation

AVs will influence the mobility of traveling. Truong et al. (2017) proposed that AVs will possibly improve the mobility for those who couldn't drive, such as individuals too young or too old. They measured this gap by generating entirely new trips for these groups. The study attempted to categorize the impact of AVs on travel demand into different age ranges. This is a reasonable assumption; in addition, other assumptions could be used in determining the AVs influence, such as categorizing them into different income groups or different regions. According to their results, around 4.14% new trips were generated by AVs over all age groups and this did not consider the trips shift from other modes.

Besides the improvement of mobility with AV deployment, the benefit of enhancing a driver's user experience may also increase their willingness to travel. Bierstedt et al. (2014) proposed an insight that enhancing user experience with AVs may make AV owners travel more than they do now. They list previous research about negative impacts of driving, such as mental stress while driving in urban areas (Automotive News, 2013) and physical damage like muscle cramps or back pain (Safety Services Company, 2009). According to the AV definition from NHTSA, a level three or level four automation may significantly reduce the responsibility for drivers. This research, conducted by Jane et al. (2014), suggested that AVs will significantly reduce the stress that drivers currently experience.

Autonomous vehicles' behavior

Benefiting from automation, AVs have several aspects that behave differently than conventional vehicles. Litman (2014) suggested that AVs could allow motorists to rest and work while driving, reduce intersection stops and narrow lanes, and find parking by itself. These benefits could potentially reduce driver stress, increase road capacity and reduce parking costs due to more efficient parking.

Zhang et al. (2015) used a discrete event simulation (DES) approach to evaluate the impact of SAVs on urban parking. They used three different parking price scenarios to examine the tradeoffs between parking fees, VMT generation and average waiting time. Their results show that a 5% penetration rate of SAV will reduce approximately 4.5% of parking land use. In addition, the parking demand would also be influenced by road congestion and average waiting time, which may result in parking shifts to adjacent travel analysis zones (TAZs). Kloostra et al. (2016) suggested that AVs might have different behaviors than traditional vehicles, such as self-parking. They generated additional trips in their model to assign AVs to park in the nearest space outside of the center area.

Levin et al. (2015) proposed a capacity based on the classic Greenshield's speed-density relationship. They also assumed the jam density to be a function of the proportion of AVs on the road because AVs generally will require less car-following distance. Kim et al. (2015) followed the function of capacity related to headway to determine the capacity on the road with different proportions of AVs. This method was first presented by Yokota et al. (1998); they presented a conceptual model to reflect the influence of headway in a Q-V model. Since the AVs will potentially reduce the car-following distance, different proportions of AVs on the road will have a different average headway, which means this headway Q-V model could apply to an AV scenario's road capacity estimation. Patel et al. (2016) borrowed a car-following model from Levin and Boyles (2015) to predict the safe car-following distance as a function of reaction time. According to their assumption of AV reaction time and vehicle length, a fundamental diagram of flow density relationship is shown in Figure 1.

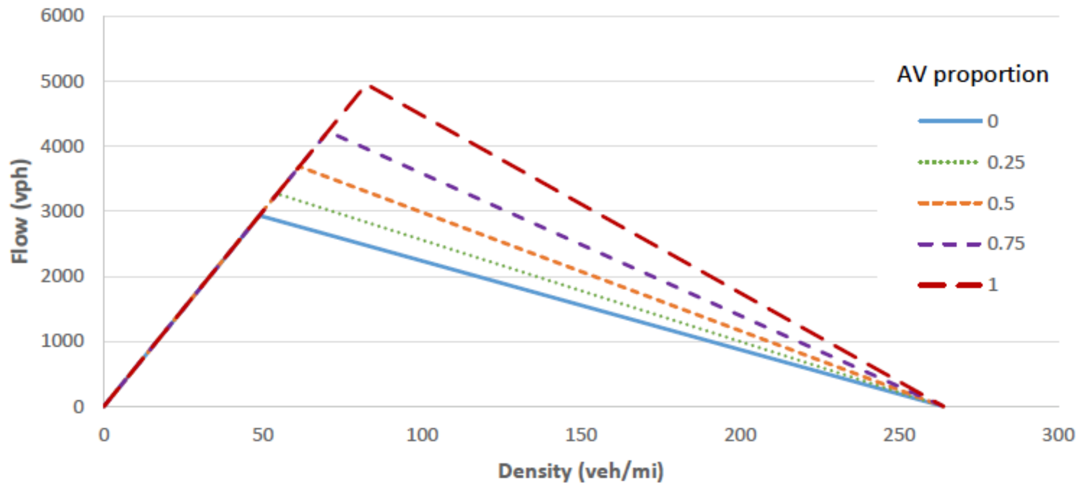


Figure 1 Flow density relationship with proportion of AVs (Patel et al., 2016).

Chen et al. (2016) proposed an extension version of the household activity pattern problem (HAPP) model. Their results show that the deployment of AVs will provide a wide range of activities to be performed in-home, out-of-home and potentially in-vehicle. Gwilliam (1997) mentioned a conceptual framework that yields important insights into the nature of travel time (TT) savings. He said that value of time (VOT) savings should be related to the value of activity with which it is associated; this could apply to AVs, in that different travel purpose could have different in-vehicle time reduction.

Nord et al. (2017) recommended developing similar policies to those of conventional vehicles, such as high occupancy (HOV) vehicle lanes and toll lanes, which allow jurisdictions to dedicate for special use.

Chapter 3: Implementation of Autonomous Vehicles in MSTM

Introduction

The Maryland Statewide Transportation Model (MSTM) is a classic four-step model built for the Baltimore-Washington metropolitan area. This thesis will introduce a new method to integrate AVs as a new travel mode. This method will be more efficient in terms of time, compared with building a new model like those in the previous literature. A separation and aggregation of model runs is the core concept of this method, which essentially reproduces the four-step procedure for the combination of AVs and conventional vehicles.

Methodology

Based on previous research on AV market penetration, experts believe AVs are likely to be on the road between the 2020 and 2030. This thesis integrates AVs into a four-step model with a predicted 2030 data set. However, the objective of this thesis is also interested in the impacts of different AV penetration rates. Thus, this thesis will consider three different penetration rates in the base scenario to compare the impact; then one penetration rate will be applied to different development scenarios.

To integrate AVs into the current four-step model, the first step is to integrate the AV's characterization into the trip generation part. The travel demand will increase due to the benefits of AVs. As Truong et al. (2017) mentioned in their paper, total trips will increase approximately 4.14% if AVs replace traditional vehicles. This thesis will take their results as reference and modify the trip generation model. This model only takes the motorized trips share into consideration, since non-motorized trips, such as walk and bike trips, are pre-determined by an external model. In-vehicle time change is pre-determined by different travel purposes and different income groups.

Assumptions

As mentioned in the previous chapter, Lavasani et al. (2016) and Bansal et al. (2016) showed opposite results of AV pricing influence in their research. Since there are two different methods showing opposite results on the influences of AV prices and willingness to pay, this thesis will not take the willingness to pay or AV initial cost into consideration. Since AVs are still in the testing stage, their behavior may vary with the development of government regulations on AVs and their performance data has mostly remained confidential. Although some research has made predictions on AVs' behavior, some benefits, like in-vehicle time utilization, have not been discussed yet. Therefore, the following assumptions about in-vehicle time utilization, road capacity and parking cost change have been made:

1. In order to avoid the uncertainty of semi-automated vehicles, where drivers may choose using the assistant system or not, in this thesis all the AVs are assumed to be level four (NHTSA) fully-automated vehicles.
2. The deployment of autonomous vehicles will liberate driver's hands and allow them make use of the time they previously used to drive. Since the utilization of time is different for different people and may also be different under different trip purposes, the utility of the in-vehicle time has been divided for different income groups and different trip purposes. The use of in-vehicle time in the model is reflected to reduce the in-vehicle time cost in the utility function of each travel mode. There are 18 different trip

purposes in this model and most of them are assumed to have an average of 50% reduction in in-vehicle time. Home-based work trips have a reduction of in-vehicle time from 50% to 80%, because drivers are allowed time to do their jobs during the work trip; this use of time usually has the most value, especially for the high-income group. However, this thesis only gives home-based school trips a 20% reduction in in-vehicle time because during these trips, parents usually will be interacting with children; this interaction would not be influenced by whether they are driving or not. Therefore, the value of the time will be much less.

3. Due to the automation ability, AVs will be available to perform an additional trip to find a proper parking lot with less parking fees. The parking demand will decrease especially in the central area. This thesis makes an assumption to reduce parking fees 50% for AVs.
4. This thesis assumes the capacity will change accordingly with respect to different adoption rates of AVs. By introducing the AVs, the car-following distance has decreased; therefore, the road capacity will increase. In the original model, the headway including car length is 16 meters under the maximum flow situation. This model assumes that AVs will reduce reaction time by 50% compared with a human driver. The human is assumed to have a reaction time of 1.0 second.

Method

A traditional four-step model has four major procedures: trip generation, trip distribution, mode choice and traffic assignment. Since AVs will potentially influence the trip demand, road capacity, parking demand and travel cost function, they need to be integrated from the start of the model. This thesis applies a parallel model run method to easily integrate AVs.

First, two of the same models are created, which are assigned to AVs and conventional vehicles; everything is the same for both, including the inputs. Then, the trip generation model in the AV's version is modified by adding a parameter to represent the AV; trip generation model in the conventional vehicle's version also adds a parameter, respectively. The sum of those two parameters is equal to one, which helps divide the generated productions and attractions into two parts; together they will equal the original total trips. An additional travel demand parameter is added to AV's version in order to represent the influence that AVs bring to the travel demand side.

Then, two-part productions and attractions go through the trip distribution separately. Since the trip distribution only distributes them by calculating the zone-to-zone travel time cost, there is no need to change this procedure because productions and attractions are proportionally changed. This means the generated trips will also be proportional with respect to the AV penetration rate.

After the trip distribution, the trips again enter into two different mode choice models. One has the same parameters and model structure as the original one. Another one has added a new parameter into utility functions, which include drive along and shared drive (HOV2, HOV3+). Since parking cost is an input of mode choice model, the parking cost is also changed in the AV's version of mode choice. This parameter serves as an in-vehicle time reduction indicator in utility function of all car modes.

Last, two sets of trip tables are shown as outputs after the previous three steps. Both of them contain trip tables by mode choice and trip tables by purpose and income groups. In this last procedure, two sets of trip tables are aggregated into one set that represents the total trips with a proportion of AVs. Then, this trip table set is applied to the traffic assignment model and produces the final results after the model run. Figure 2 will show the overview of the integration method.

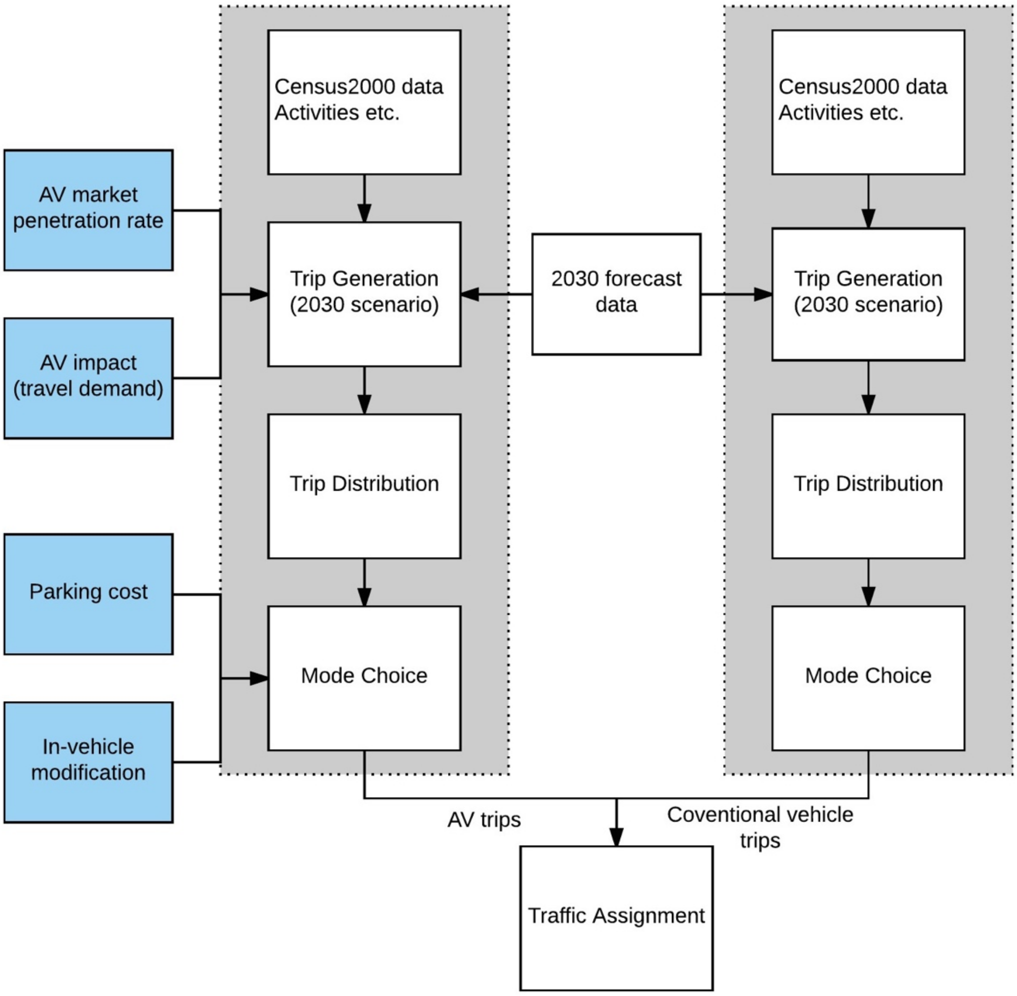


Figure 2 Method for AV's integration.

Four-step Model Modification

MSTM is a regional planning model which includes Maryland, Washington, D.C., Delaware and a part of Virginia. In total, 18 different trip purposes and 11 different travel modes have been defined in the model. Trip purposes include home-based work (HBW) with five income groups, home-based shopping (HBS) with five income groups, home-based other (HBO) with five income groups, home-based school

(HBSc), non-home-based work (NHBW) and other-based other (OBO). Since this thesis is dedicated to integrating AVs, transit will remain within the same parameters, so no changes will be made. The travel mode related to cars are drive along (DA), shared drive (SR2) and shared drive (SR3+).

Trip generation

In the MSTM trip generation model, trips are generated by different trip purposes and income groups. First, the activities density has been calculated for each zone, which are later used in trip attraction generation. Then, income shares of each trip purpose have been calculated by applying existing home-based work (HBW) attraction shares; other income shares by purpose are scaled by its own pre-defined rate and HBW attraction shares by income.

In the production and attraction generation portion, a modified model is introduced:

$$\left.\begin{array}{c} P_{p_i} = \sum_{w=0}^{3} \alpha_{iw} * wk_{wi} * HBW_i * (1 - D) * \beta \\ A_{pi} = T_{p_a} * \theta_{p_i} * \beta \end{array}\right] for\ p_i \in (1,5)\ i \in (1,5)$$

$$\left.\begin{array}{c} P_{p_i} = \sum_{s=1}^{5} \alpha_{is} * siz_{si} * HBS_i * \beta \\ A_{pi} = T_{p_a} * \theta_{p_i} * \beta \end{array}\right] for\ p_i \in (6,10)\ i \in (1,5)$$

$$\left.\begin{array}{c} P_{p_i} = \sum_{s=1}^{5} \alpha_{is} * siz_{si} * HBO_i * \beta \\ A_{pi} = T_{p_a} * \theta_{p_i} * \beta \end{array}\right] for\ p_i \in (11,15)\ i \in (1,5)$$

$$\left.\begin{array}{c} P_{p_i} = \sum_{i=1}^{5}\sum_{w=0}^{3} \alpha_{iw} * wk_{wi} * NHBW_i * \beta \\ A_{pi} = T_{p_a} * \theta_{p_i} * \beta \end{array}\right] for\, p_i = 17$$

$$\left.\begin{array}{c} P_{p_i} = \sum_{i=1}^{5}\sum_{s=1}^{5} \alpha_{is} * siz_{si} * HBSCH_i * \beta * \delta \\ A_{pi} = T_{p_a} * \theta_{p_i} * \beta * \delta \end{array}\right] for\, p_i = 16$$

$$\left.\begin{array}{c} P_{p_i} = \sum_{i=1}^{5}\sum_{s=1}^{5} \alpha_{is} * siz_{si} * NHBO_i * \beta \\ A_{pi} = T_{p_a} * \theta_{p_i} * \beta \end{array}\right] for\, p_i = 18$$

Where:

α_{iw}: coefficient of household (HH) in income group *i,* with worker count *w;*

wk_{wi}: number of HH with worker count *w* in income group *i;*

HBW_i, HBS_i etc.: motorized share for each purpose in income group *i*;

D: trip production dampening coefficient;

β: autonomous vehicles coefficient;

δ: coefficient to remove school bus trips;

T_{p_a}: total attractions of purpose *p;*

θ_{p_i}: attraction share of income group i in purpose *p;*

α_{is}: coefficient of HH size in income group *i* with size count *s;*

siz_{si}: number of HH size with size count *s* in income group *i.*

The parameter β could change depending on different trip purposes and different income groups; however, no study has been done on how the influence will vary from different trip purposes and income groups. Therefore, this thesis assumes parameter β to be 5%.

Trip distribution

In the trip distribution step, a gravity model is used to determine the number of school trips between origins and destinations. This gravity model is formed by productions multiplying attractions and friction factors, as shown below:

$$T_{ij}^{k} = P_{i}^{k} * A_{j}^{k} * F_{ij}^{k} / \sum_{j} (A_{j}^{k} * F_{ij}^{k})$$

Where:

T_{ij}^{k}: trips for purpose k between production zone i and attraction zone j;

P_{i}^{k}: productions for trip purpose k in zone i;

A_{j}^{k}: attractions for trip purpose k in zone j;

F_{ij}^{k}: fraction factors for trip purpose k between zone i and j.

The number of all other kinds of trips from each origin to destination is determined by a destination choice model, which has the same discrete choice model structure and utility function used in mode choice. The only difference is that they are using different parameters. Discrete choice model structure and utility functions are demonstrated in the mode choice part. After computing every exponent of utilities for each nest level, Log Sum is computed for each trip and is used to determine OD pairs for each trip.

Mode choice

Mode choice procedure helps to assign personal trips to different travel modes. The MSTM uses a nested logit model to calculate the utility of each mode and determine the mode choice for each trip. Travel modes are divided into two major nests as auto and transit, as well as one sub-nest under auto trip and two sub-nests under transit trips. The nested logit model structure is shown in Figure 3.

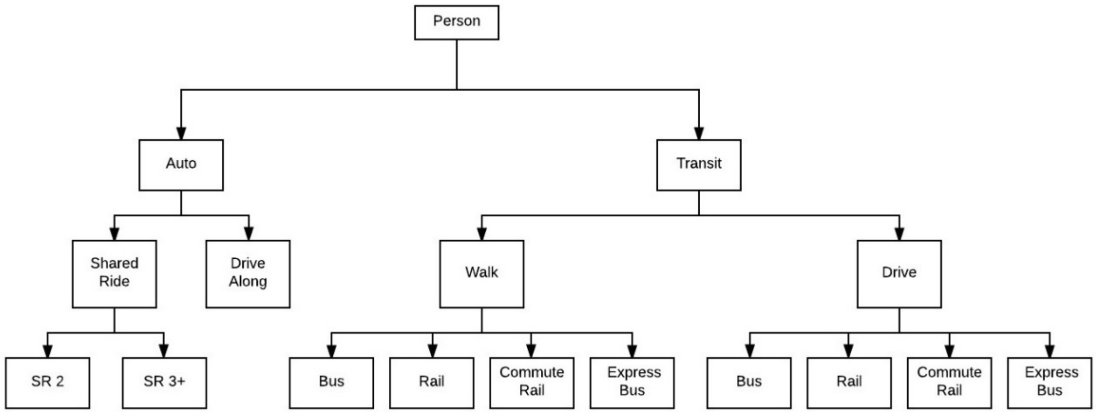


Figure 3 Mode choice model structure.

In the utility function of cars, the cost of in-vehicle time and parking cost are considered. Therefore, changes have been made on utility functions to represent the AV's characteristics. The modified utility functions for autos are:

$$U_{DA} = \{c_{ivt} * t_{SOV} * \alpha + c_{term} * T_{ij} + c_{opcost} * D_{SOV} * C_{op} + c_{pcost} * (Toll_{SOV} + C_{wkp}(i))\}/c_{na}$$

$$U_{SR2} = \left\{c_{ivt} * t_{HOV} * \alpha + c_{term} * (T_{ij} + 1.1) + c_{opcost} * D_{HOV} * \frac{C_{op}}{2} + c_{pcost} * \left(Toll_{HOV} + \frac{C_{wkp}(i)}{2}\right) + B_{SR}\right\}/c_{nsr}/c_{na}$$

$$U_{SR3} = \left\{c_{ivt} * t_{HOV} * \alpha + c_{term} * (T_{ij} + 2.5) + c_{opcost} * D_{HOV} * \frac{C_{op}}{avg} + c_{pcost} * \left(Toll_{HOV} + \frac{C_{wkp}(i)}{avg}\right) + B_{SR} + B_{SR3}\right\}/c_{nsr}/c_{na}$$

Where:

c_{ivt}: coefficient of in-vehicle time;

t_{SOV}: SOV in-vehicle time;

α:in-vehicle time reduction rate;

c_{term}: coefficient of terminal time;

T_{ij}: terminal time from origin i to destination j;

c_{opcost}: coefficient of auto operation cost;

D_{SOV}: SOV travel distance;

C_{op}: auto operation cost;

c_{pcost}: coefficient of parking cost;

$C_{wkp}(i)$: parking cost of zone i;

B_{SR}: bias of shared drive;

c_{nsr}/c_{na}: nesting coefficient of shared drive/auto.

The in-vehicle time reduction rate is pre-determined by different trip purposes and income groups. Table 1 shows the reduction rate for each purpose with different income categories.

Table 1 In-vehicle Time Reduction Rate

Purposes	Rate	Purposes	Rate
HBW1	0.8	HBS5	0.8
HBW2	0.8	HBO1	0.8
HBW3	0.8	HBO2	0.8
HBW4	0.8	HBO3	0.8
HBW5	0.8	HBO4	0.8
HBS1	0.8	HBO5	0.8
HBS2	0.8	HBSc	0.8
HBS3	0.8	NHBW	0.8
HBS4	0.8	OBO	0.8

Traffic assignment

In the traffic assignment step, since transit networks and highway networks are two separate systems not affecting each other, this thesis only introduces the highway assignment.

There are two major steps in highway assignment. First, since the model is not a dynamic model, the travel time for each link is assumed to be the time in minutes needed to pass this link under congestion situations. All trips with different purposes, different income groups and travel modes have been assigned to four value of time (VOT) groups. The initial minimum travel cost has been calculated for each link and the facility type of links is classified into four classes. Then, trips have been respectively assigned to each link. The first step is shown below:

$$T_{io} = 60 * D_i / v_{ci}$$

$$C_{ia} = T_{io} + \frac{C_{tolli}}{VOT_a} + 0.25 * D_i$$

$$C_{ib} = T_{io} + \frac{C_{tolli}}{VOT_b} + 0.25 * D_i$$

$$C_{ie} = T_{io} + \frac{C_{tolli}}{VOT_e} + 0.25 * D_i$$

$$C_{if} = D_i * \frac{60}{v_{FFi}} * 0.5 + T_{io} * 0.5 + \frac{C_{tolli}}{VOT_f} + 0.25 * D_i$$

Where:

T_{io}: travel time for link *i*;

D_i: distance of link *i*;

v_{ci}: congestion speed of link *i*;

C_{ia}: travel cost of link i for VOT group *a*;

C_{tolli}: toll cost of link *i*;

v_{FFi}: free flow speed of link i.

Then, the travel time for each link in different classes is recalculated based on current assignment. After that, the new travel cost for each link is recalculated. The second step is shown below:

$$T_{1i} = Min\{T_{io} * \left(1 + 0.7 * \left(\frac{V}{C}\right)^8\right), T_{io} * 100\}$$

$$T_{2i} = Min\{T_{io} * \left(1 + 0.7 * \left(\frac{V}{C}\right)^8\right), T_{io} * 100\}$$

$$T_{3i} = Min\{T_{io} * \left(1 + 0.7 * \left(\frac{V}{C}\right)^8\right), T_{io} * 100\}$$

$$T_{4i} = T_{io}$$

Where:

T_1: travel cost of link *i* in class 1;

V: total volume of link *i;*

C: capacity of link *i*.

Chapter 4: Scenarios Build

This thesis has utilized a draft base scenario built at the University of Maryland's National Center for Smart Growth (NCSG). In total, six scenarios have been introduced by this thesis, including base scenario 2030 (Base), base scenario with 10% AV (Base10), base scenario with 30% AV (Base30), base scenario with 50% AV (Base50), base scenario with 70% AV (Base70), and base scenario with 90% AV (Base90). The following portion of this chapter discusses the background of the scenario build and the further development for AV deployment.

Draft Scenario Description

The base scenario 2030 is the original MSTM set up for 2030, which uses the census data in 2000 and other social demographic and social economic data to generate trips for the year 2007. In the base scenario 2030, the network has been changed with respect to the current network situation and forecast network modification, based on the Maryland Statewide Transportation Investment Plan. The social demographic and social economic data have also been revised to predict the situation in 2030.

Further Development

This thesis is dedicated to integrating AVs into MSTM and to analyze the impact of AVs with different market penetration. There are four different time-of-day choices for travelers to conduct their trips. In order to simplify the model runs and make the results more representative, this thesis only considers the PM peak period. The reminder of this section will introduce the newly set up for base 2030 with different market penetration rate, and the set up for other scenarios with on-market penetration rate.

Base 2030 scenarios with AVs

The base scenarios with AVs are built up based on the base 2030 scenario with additional assumptions.

Lavasani et al. (2016) predict that AVs will be available for purchase by 2025 and the AVs adoption rate will reach approximately 87% by 2060. Litman (2014) predict that AVs may be available for purchase as early as 2020 and the AVs adoption rate may vary from 70% to 90% by 2060 to 2070. This thesis chooses three different AVs adoption rates, which are 10%, 40% and 90%, to predict the potential impacts of AVs in base scenario.

Since this thesis use a method to generate trips for AVs and conventional vehicles separately, on the demand side, the trip generation for AVs' portion could be assumed as 100% adoption rate. A 5% demand increase for AV trips has been applied to the model, which is equivalent to 0.5%, 2% and 4.5%, increasing in total travel demand for 10%, 40% and 90% of AVs adoption rate.

Zhang et al. (2017) predicts that a 5% adoption rate of SAVs will decrease 4.5% of parking land in Atlanta, which means SAVs only require 10% of parking lots, compared to conventional vehicles. Since SAVs could serve multiple individuals that keep them operating on the roads, the dramatic decrease in parking demand is reasonable. However, AVs cannot reduce the parking demand except to park themselves somewhere cheaper, which will end in reducing the parking cost. This thesis assumes parking cost for AVs will reduce 50% due to their ability to self-park.

As Chen et al. (2016) predicted, the benefit of AVs may potentially provide travelers the possibility to conduct in-vehicle activities. The value of the utilization of in-vehicle time is reflected as in-vehicle time reduction in this thesis. Since the value of time (VOT) will be different for different income groups and may potentially be different for different trip purposes, the reduction rate is defined in Table 1.

A $Q = K * V$ relationship has been used to estimate the capacity change due to the impact of AVs. The results have been rounded to easily reflect the relationship of capacity change between different AVs adoption rate. This thesis only considers the capacity change on highways; the capacity of other types of facilities will remain the same because the benefit of AVs may be weakened due to the complex traffic situations. As a result, capacity will increase 5% while the adoption rate is 10%. Capacity will increase 15% while the adoption rate is 30% and will increase 25% while the adoption rate is 50%, etc.

The scenarios build for all scenarios is shown in Table 2.

Table 2 AV Scenarios Build

Scenarios	Base 2030				
Adoption Rate	10%	30%	50%	70%	90%
Road Capacity	+5%	+15%	+25%	+35%	+45%
Demand	+0.5%	+1.5%	+2.5%	+3.5%	+4.5%
Parking Cost (AV)	-50%	-50%	-50%	-50%	-50%

Chapter 5: Numerical Results and Analysis

In this chapter, the results from scenarios are presented and the analysis is discussed. This chapter is organized as follows: Section 5.1 introduces an experiment to test the method. Section 5.2 analyzes the results from base scenarios to assess the impact of different adoption rate of AVs.

Model Validation

This method of integrating AVs by dividing a four-step model into two parts is unconventional, compared with other methods. With a deep understanding of the model structure of Maryland Statewide Transportation Model, this method is proven to be theoretically correct. However, in order to make sure this method works correctly, an experimental test is set up to evaluate this method.

Two models are set up to do the validation work; one is divided into 10% of original households and 90% of original households, while another is divided into 40% of original households and 60% of original households. Everything else remains the same and both models use the method of this thesis to run. The numerical results are shown below in Table 3.

Table 3 Experimental Results

	Base			
	Original	10%	50%	MAX. Difference
Total Trips	66098126	66098126	66098126	0%
Transit Trips	3618074	3618074	3618074	0%
VMT	119530423	119530423	119530423	0%

The results show that there is no difference between all scenarios among all the statistic results. Since the difference is 0%, it is safe to say that this method could produce the same results as the original four-step model. Thus, the results of integrating AVs by using this method could represent the results from a four-step model that originally has AVs in its mode choice.

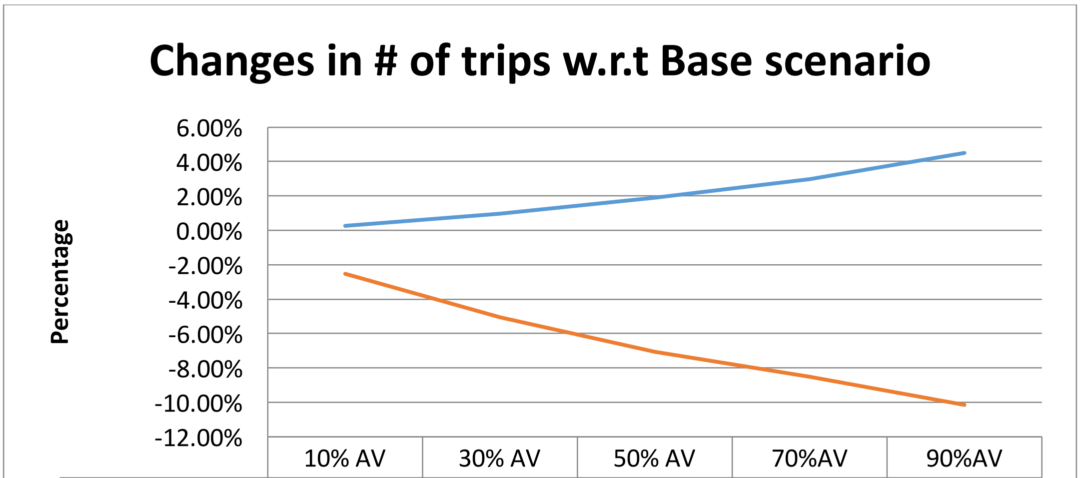
Base Scenarios Analysis

The statistic results of base 2030 scenarios are shown in the Table 4.

Table 4 Base 2030 AV Scenarios Statistic Results of Changes

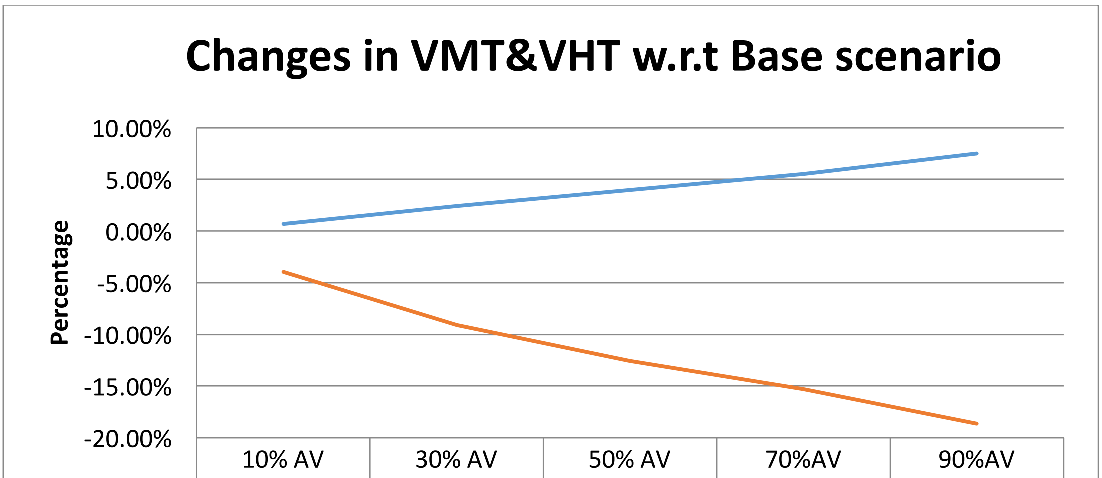
Scenario	Base 2030				
Adoption Rate	10%	30%	50%	70%	90%
VMT	+0.71%	+2.40%	+4.01%	+5.51%	+7.49%
VHT	-3.96%	-9.10%	-12.54%	-15.27%	-18.64%
VMT Highway	+1.75%	+5.04%	+7.96%	+10.80%	+14.37%
VHT Highway	-1.20%	-3.87%	-5.24%	-5.86%	-6.69%
Transit Trips	-2.53%	-5.05%	-7.06%	-8.52%	-10.16%
Total Trips	+0.27%	+0.97%	+1.89%	+2.99%	+4.51%
Avg. Distance	+0.43%	+1.41%	+2.07%	+2.44%	+2.85%
Avg. Travel Time	-4.22%	-9.98%	-14.16%	-17.73%	-22.15%
Avg. Speed	+4.86%	+12.65%	+18.92%	+24.52%	32.12%
Avg. Highway Speed	+2.99%	+9.26%	+13.94%	+17.69%	+22.57%

In order to better interpret the results, three sets of results have been chosen to visualize below.



	10% AV	30% AV	50% AV	70%AV	90%AV
Total Trips	0.27%	0.97%	1.89%	2.99%	4.51%
Transit Trips	-2.53%	-5.05%	-7.06%	-8.52%	-10.16%

Figure 4 Changes in number of trips



	10% AV	30% AV	50% AV	70%AV	90%AV
VMT	0.71%	2.40%	4.01%	5.51%	7.49%
VHT	-3.96%	-9.10%	-12.54%	-15.27%	-18.64%

Figure 5 Changes in VMT & VHT

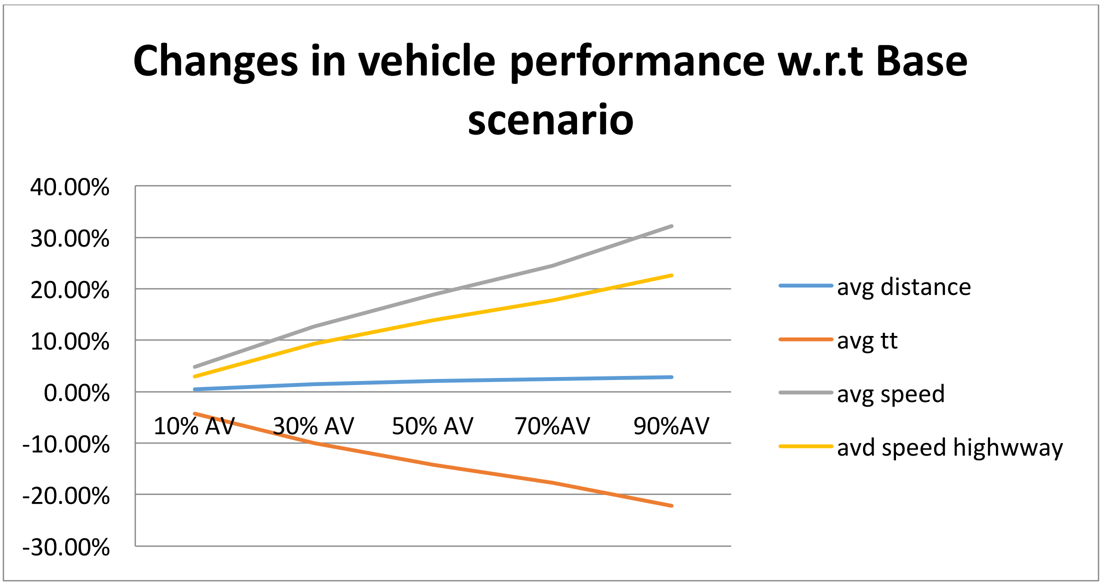


Figure 6 Changes of vehicle performance in the network

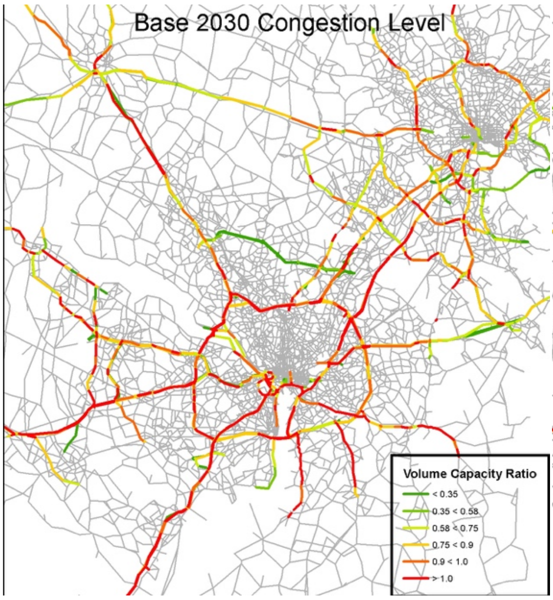
From Figure 4, we can see that the changes in total trips are linear with the adoption rate of AVs increasing. This result shows that trips will increase more when AV adoption rate become higher. The curve of transit trips shows that transit trips were constantly shifting to auto trips with the increase of AVs adoption rate. However, the slope is obviously becoming smaller when AV adoption rate become larger. This is because the network first has a larger base number of transit trips; since transit trips constantly shift to auto trips, the base number of transit trips has decreased so less transit trips will shift to auto trips. In addition, number of transit trips with less utilities will always be larger than the number of transit trips with more utilities. This will result in decreasing influence from AV's benefits to remaining transit riders when the AV adoption rate is increasing.

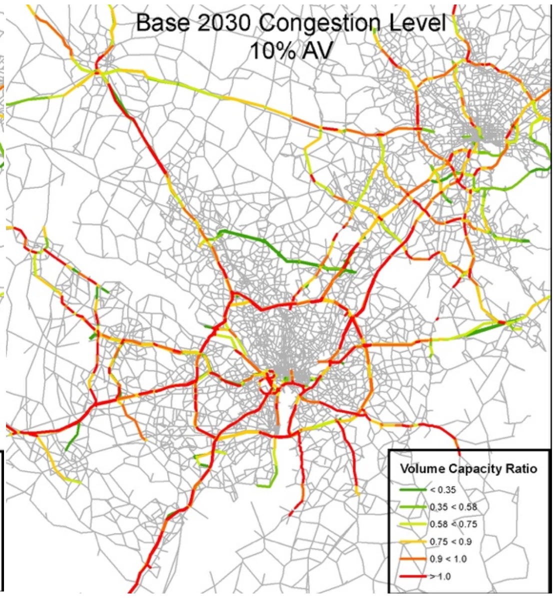
From Figure 5, we can see some of the same results from Figure 4. It is obvious that with an increasing AVs adoption rate, Vehicle Mile Traveled (VMT) will also increase respectively and Vehicle Hour Traveled (VHT) will decrease respectively. The traffic condition was assumed to be better since AVs will increase road capacity and results match the assumptions. These results demonstrate that people will tend to travel longer distances if they have AVs.

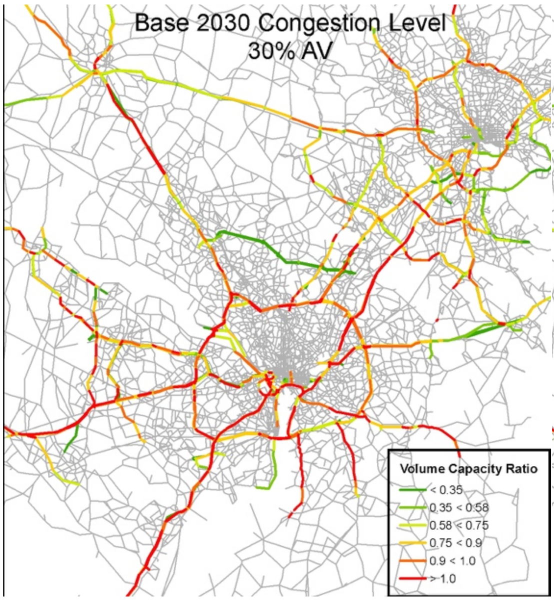
In Figure 6, we can observe that average travel distance increases constantly, which indicates that AVs surely will attract people to travel longer because of the assumption that people will have more value while traveling in AVs. We can also observe that average travel speed increases constantly due to the benefit of increasing capacity. One interesting result is that the average speed overall has a larger increasing slope than average highway speed. This result shows us that the capacity change due to the benefit of decreasing car-following distance by AVs will have a larger impact on local roads than on highways. This is because local roads will be more congested in most situations, which makes capacity increasing more important. We will be able to improve the results after we get more precise behavior data from AVs and modified network capacity.

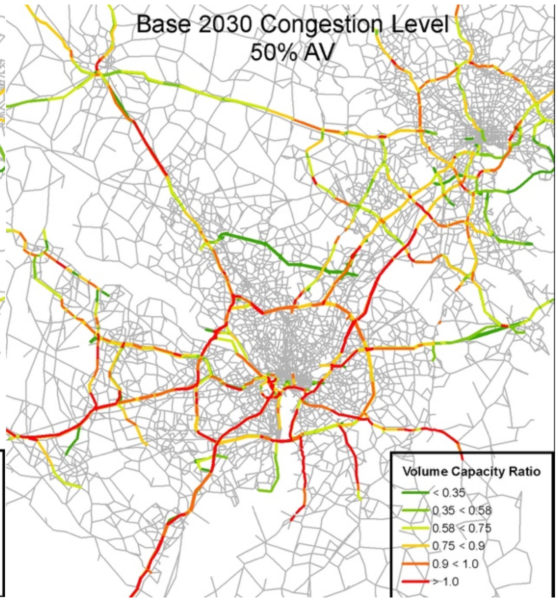
Over all, the comparison of six scenarios with different AV adoption rates show that AV will increase travel demand and bring better traffic conditions when the adoption rate becomes higher. The average travel speed will increase with the AV adoption rate increasing.

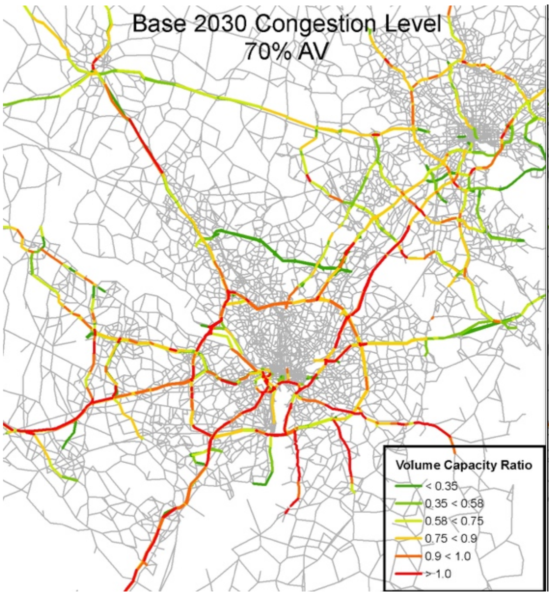
The network congestion maps are shown in Figure 7.


Base 2030 Congestion Level
Volume Capacity Ratio
< 0.35
0.35 < 0.58
0.58 < 0.75
0.75 < 0.9
0.9 < 1.0
> 1.0


Base 2030 Congestion Level
10% AV
Volume Capacity Ratio
< 0.35
0.35 < 0.58
0.58 < 0.75
0.75 < 0.9
0.9 < 1.0
> 1.0


Base 2030 Congestion Level
30% AV
Volume Capacity Ratio
< 0.35
0.35 < 0.58
0.58 < 0.75
0.75 < 0.9
0.9 < 1.0
> 1.0


Base 2030 Congestion Level
50% AV
Volume Capacity Ratio
< 0.35
0.35 < 0.58
0.58 < 0.75
0.75 < 0.9
0.9 < 1.0
> 1.0


Base 2030 Congestion Level
70% AV
Volume Capacity Ratio
< 0.35
0.35 < 0.58
0.58 < 0.75
0.75 < 0.9
0.9 < 1.0
> 1.0

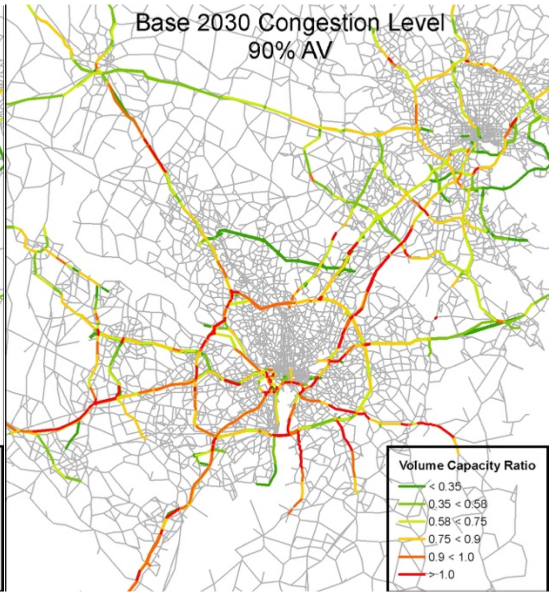

Base 2030 Congestion Level
90% AV
Volume Capacity Ratio
< 0.35
0.35 < 0.58
0.58 < 0.75
0.75 < 0.9
0.9 < 1.0
> 1.0

Figure 7 Base scenarios congestion map

From the congestion map we can see that base10 does not improve much with respect to the base scenario. However, as the AVs adoption rates increase, the traffic conditions will improve respectively. In order to better show what consequences AVs may bring to network, these congestion maps only draw highway networks with volume over capacity ratio. Thus, AVs will increase traffic conditions in highways because we increase their capacity.

Chapter 6: Conclusion and Discussion

The method this thesis uses can help generate relatively accurate results to assess the impact of AVs. Despite the disadvantages of a four-step model, we can still assess the impact with a different proportion of AVs on the road.

In general, AVs will increase travel demand, which will result in increasing trips and VMT. The average travel distance will increase when AVs adoption rate increases, because AVs will attract travelers to travel longer. The average speed will increase when the AV adoption rate increase. The VHT will decrease due to the implementation of capacity increasing and traffic conditions will improve, especially when the AV adoption rate reach a high level. With the increase of the AV adoption rate, transit trips will shift to auto trips and the total trips will increase due to the demand increasing. Overall, AVs will eventually help improve the traffic conditions and will increase traveler's willingness to drive.

A critical step in the future research is to better modify AVs' characteristics with more real data from industries or technology companies. Thus, the impact of AVs can be predicted more precisely than now. More information of AVs' behavior in urban areas can help to better predict their performance on local roads, which can tell us more accurately at which point of the AV adoption rate will the entire traffic network perform better. The efforts in this thesis can also shift to an advanced traffic model, such as ABM, which can provide better prediction.

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