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Impacts of Connected and Autonomous Vehicles on Transportation Demand and Land Use

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Impacts of Connected and Autonomous Vehicles on Transportation Demand and Land Use

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ENGINEERING

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Chapter 1
Impacts of Private Autonomous and Connected Vehicles on Transportation Network Demand in the Triangle Region, NC

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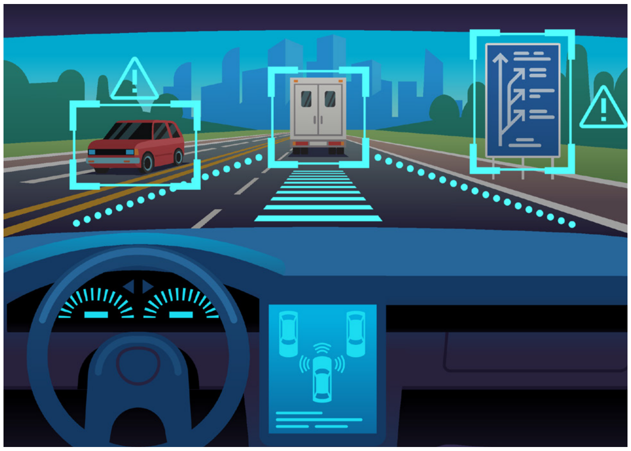
1.1 Introduction

Autonomous and connected vehicles are expected to bring profound changes to human mobility within the coming few decades. Automation and connectivity have the potential to improve roadway safety, reduce energy consumption, and provide better access to destinations for a number of user groups. Several studies have argued for a high market penetration rate (MPR) of advanced vehicle technologies in the next twenty years. As an example, the National Cooperative Highway Research Program (NCHRP) Project 20-102(09) has suggested that highly automated vehicles are likely to be present in large numbers on highways before 2038 (Zmud et al. 2018). At the same time, many possible future scenarios have been envisioned for the operation and services provided by these vehicles. At one extreme, adoption of emerging vehicle technologies could be dominated by privately-owned vehicles; in this case, autonomous vehicles (AVs) or connected and autonomous vehicles (CAVs) will remain a luxury item for people who can afford them (Zhang et al. 2018; Bansal et al. 2016). At the other extreme, shared vehicle fleets are envisioned to have significantly higher market shares compared to privately-owned vehicles, potentially participating in mobility as a service (MaaS) platforms (Krueger et al. 2016; Shen et al. 2017). While it is highly uncertain in what form transportation services will be provided in the future, technological advances will certainly induce fundamental changes in transportation mobility, which in turn is expected to transform existing land use and development patterns (Zhang and Guhathakurta 2018).

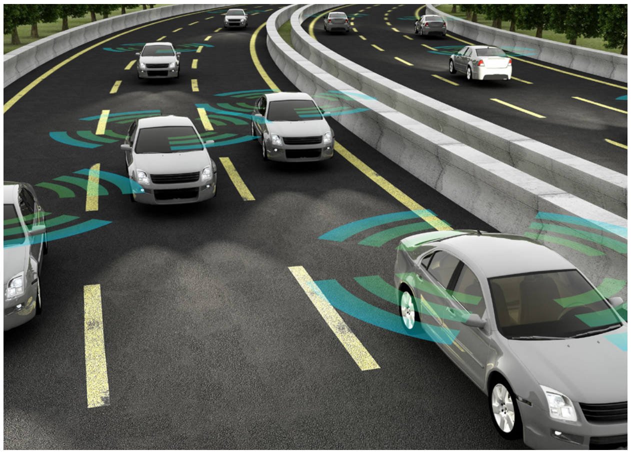
A number of studies have focused on the impacts of AVs and CAVs on different aspects of transportation systems and travel behavior. Several studies have reported expected changes



in individual travel demand (Truong et al. 2017; Harper et al. 2016), freight services (Tsugawa et al. 2011), roadway capacity (Le Vine et al. 2017), energy use and emissions (Harper et al. 2018), and traffic safety (Koopman and Wagner 2017). Studies have also examined the fleet size of shared autonomous vehicles required to serve different types of travel demand (Fagnant and Kockelman 2015; Lu et al. 2018) and the possibility of improving public transit services by providing first mile/last mile services with AV technology (Mccauley 2017).

While focusing on a single aspect of these emerging vehicle technologies is critical for under- standing their effect in depth, it is also important to bring the possible impacts together within a single framework to provide urban and transportation planners with a network-level overview of the effects of vehicle automation and connectivity on their jurisdictions. A few researchers have used agent-based simulations to predict the impacts of private or shared AV and CAV adoption on traffic in particular cities (Fagnant and Kockelman 2015; Auld et al. 2017), while others have predicted the network-level effects of vehicle autonomy and connectivity by incorporating relevant scenarios into regional travel demand models (Truong et al. 2017; Zhao and Kockelman 2018; Meyer et al. 2017; Nair et al. 2018; Kim et al. 2015). Due to the uncertainties associated with emerging vehicle technologies and their deployment, it is difficult to make precise predictions about the future. Therefore, all previous studies that have focused on city-wide or regional impacts of automation and connectivity have analyzed several alternative future scenarios.

The goal of this research is to improve our understanding of the long-term network-level effects of privately-owned autonomous



and connected vehicles. The study explores the potential changes in vehicle-kilometers traveled (VKT), vehicle-hours traveled (VHT), average speed, and other transportation network performance indicators in the case where personal AVs and CAVs dominate the market compared to shared vehicle fleets. Focusing on a 25-year time horizon, market penetration rate (MPR) scenarios of personal AVs and CAVs along with results from microscopic mixed-traffic simulations and travel behavior assumptions are incorporated into a regional travel demand model. This study differs from previous research in a multitude of ways. First, contrary to general ca- pacity assumptions introduced in previous research (Zhao and Kockelman 2018; Childress et al. 2015), this study utilizes estimates of freeway and highway capacity that are based on microscopic simulation analysis that considers the interactions of AVs, CAVs, and traditional human-driven vehicles. Unlike AVs, CAVs can communicate with other CAVs in the surrounding traffic using vehicle-to-vehicle communications and with the infrastructure using vehicle-to-infrastructure com- munications, which enables them to operate safely with smaller headways. These technological differences between AVs and CAVs as well as their interactions in mixed-traffic conditions are accounted for in this study through the use of dynamic car-following algorithms in a microscopic simulation platform. The majority of past studies have focused on the impacts of either AV or CAV and have not considered scenarios with mixed-traffic conditions. Hence, those studies have missed the possible implications arising due to the interactions between different vehicle types (Zhao and Kockelman 2018; Kockelman et al. 2017; Childress et al. 2015; Nair et al. 2018).

In addition, unlike previous research (Truong et al. 2017; Zhao and Kockelman 2018; Meyer et al. 2017), this study specifically focuses on a future where shared autonomous and connected vehicles do not capture a significant market share. The study is intended to inform practitioners about the network implications of such a prospect. Studies looking into a future where shared services are dominating the market are also needed to provide practitioners with a more comprehensive picture of the potential network effects of automation and connectivity and guide their future efforts, including private sector partnerships and pilot projects.

To fulfill the study's objective, a number of travel behavior, technology adoption, and highway capacity scenarios for the year 2045 are modeled using the Triangle Regional Model (TRM), the regional macroscopic travel demand model for the Triangle Region, North Carolina (NC). The TRM is a traditional four-step travel demand model and resembles the majority of existing regional models in the US. In this regard, this study can serve as an illustration for transportation and urban planners who are interested in understanding the impacts of vehicle automation and connectivity in their region. In addition, the study demonstrates how the results from micro and macro simulation tools can be integrated to widen our views on the future of AV and CAV technologies.

The results of this research will assist planners and engineers in metropolitan planning organizations (MPO) and departments of transportation (DOT) to make informed decisions regarding future planning, new policies and regulations, highway infrastructure investments, and strategic partnerships with the automotive industry and technology development companies. Such informed decisions will lead to improvements in the performance of transportation networks and the quality of life of users and communities in the long term.

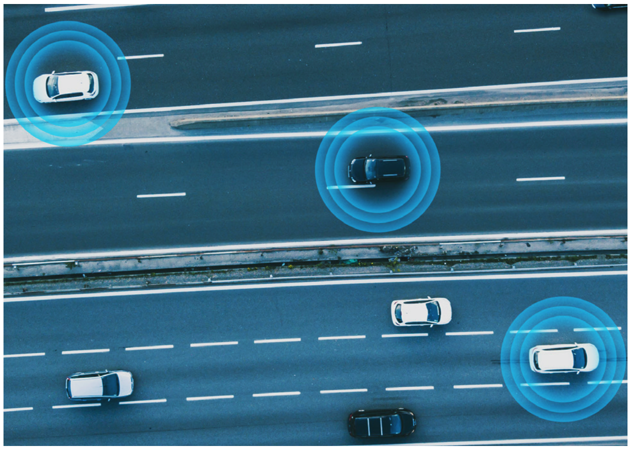
The next section focuses on findings from the relevant literature. Subsequent sections describe the study area and provide background on the travel demand model used in this study. The description of the study methodology follows, including the key assumptions and the development of relevant AV and CAV scenarios. Next, the results and key finding of the sensitivity analysis are discussed. Finally, the last section summarizes the study and discusses conclusions, limitations, and related future efforts.

1.2 Literature Review

Previous studies have used trip-based as well as activity-based and agent-based travel demand models in order to simulate the regional or local impacts of privately owned and shared AVs and CAVs on transportation network demand (Soteropoulos et al. 2019).

Zhao and Kockelman (2018), Kockelman et al. (2017), and Nair et al. (2018) examined the network-level impacts of advanced vehicle technologies in Texas by introducing modifications to the traditional four-step demand models. Zhao and Kockelman (2018) simulated nine different scenarios in the four-step travel demand model for Austin, Texas, related to privately-owned CAVs and shared AVs for the year 2020. Methodologically, the study introduced a simplified mode choice model with four modes (traditional auto, shared AVs, private CAVs, and bus) and made assumptions about the model parameters related to private CAV and shared AV choice. The study also assumed a 25%-75% decrease in the value of travel time (VOTT) for private CAV and shared AV, and a 0%-100% decrease in parking costs for private CAVs (assuming that the owners could send the vehicles to lower-cost parking facilities) compared to traditional vehicles. Results from Zhao and Kockelman (2018) indicated that the benefits of reduced VOTT and parking costs for private CAVs and shared AVs would increase the overall VKT (up to 19%), reduce the average travel speed (up to 33%), and consequently increase congestion. In addition, Kockelman et al. (2017) simulated the changes in demand and route choices due to the introduction of private CAVs in Texas. The authors developed a mode choice model with three travel modes (transit, driving and parking the vehicle, and CAV driving and re-positioning) using household survey data (Kockelman et al. 2017). The modified four-step

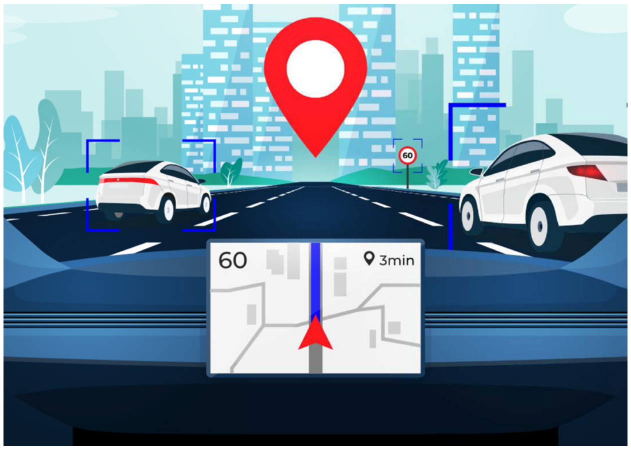
demand model was then used to simulate the morning peak traffic under different scenarios including increased highway capacity (25%-200%), increased trip generation (20%-100%, except for work trips), reduced parking costs (0% or 50% of existing cost) and reduced VOTT (Kockelman et al. 2017). The results showed that the increased MPR of CAVs would increase the total person-miles traveled (up to 271%) and



decrease average speed (up to 9%) (Kockelman et al. 2017). The study concluded that the improved capacity due to CAVs would substantially offset the effects of increased demand, while the link speed might decrease due to increased round trips made by some CAVs (Kockelman et al. 2017). Furthermore, Nair et al. (2018) provided guidelines on modifying the Dallas-Forth Worth area four-step travel demand model to incorporate the impacts of AVs and CAVs and ride-hailing (non-AV/CAV) services. Specifically, an AV/CAV ownership model was developed to be placed before the trip generation step. Increases in trip rates and trip lengths were also suggested for home-based non-work trips by households that own AV or CAV. Nair et al. (2018) used the concept of passenger car equivalence (PCE) to estimate capacity improvements from different MPR of AVs and CAVs. The PCE was assumed to be a function of the vehicle's length and distance headway. AVs and CAVs were assumed to have a shorter length than human-driven vehicles, and the distance headways were calculated based on the link's travel speed and assumed reaction time for the vehicle. The adjusted PCE was then used to modify the link capacity on different facilities. After incorporating these changes, the study tested two scenarios with 20% and 30% MPRs for AVs and CAVs. Their findings suggested that the convenience of AVs and CAVs will produce additional vehicle-miles traveled (VMT); however, the overall level of service will not deteriorate as AVs and CAVs were assumed to substantially improve roadway capacity (Nair et al. 2018).

Besides modifying four-step travel demand models, some studies have used activity-based modeling (Childress et al. 2015; Kim et al. 2015) or agent-based simulation (Auld et al. 2017) to study the impacts of private and shared AVs/CAVs. Childress et al. (2015) simulated four different scenarios in the Puget Sound activity-based transport model to study the impacts of private and shared AVs for Seattle, WA. The study assumed a 30% increase in roadway capacity and a 35% decrease in VOTT, and suggested price schemes for shared AV services. The results suggested a 20% increase in VMT for privately-owned AVs due to reduced burden of travel which encouraged people to switch from transit and walking to AV, and take longer routes for work trips. For shared AVs, the study assumed a higher cost of travel, which led to reduced average trip lengths, more shared rides, and more transit and walking trips. This resulted in an overall decrease in VMT (up to 35%) compared to their base scenario. Kim et al. (2015) conducted a similar study for Atlanta, GA, to simulate the impact of privately-owned AVs using the activity-based model of the Atlanta Regional Commission. Scenarios included 50%-100% increase in highway capacity, 0%-50% reduction in VOTT, 0%-70% reduction in operating costs, and 0-100% reduction in parking costs for private AVs. The results yielded an increase in VMT (up to 24%) and VHT (up to 12%) (Kim et al. 2015). Auld et al. (2017) used agent-based modeling to estimate the mobility impact of level 4 CAVs in the Chicago metropolitan region. The study considered a range of MPR of connected adaptive cruise control (CACC) technology (0 to 100%) and set up a number of scenarios with changes in VOTT (up to 75% reduction), roadway capacity (up to 77% increase), willingness to pay (WTP) for CACC technology ($0, $5000 and $1500), and autonomous intersections (only for 100% MPR of CACC). Auld et al. (2017) utilized the empirical function from Shladover et al. (2014) and Vander Werf et al. (2002) to update the roadway link capacity at different MPR of CACC. The link capacity was expressed as a linear function of the percentage of vehicles equipped with CACC traversing through that link (Shladover et al. 2014; Vander Werf et al. 2002). The model incorporated an extreme case with 75% reduction in VOTT and 77% increase in capacity to simulate 100% MPR of CAVs. The results suggested increases in VMT, VHT, and average travel time of 78%, 180%, and 228%, respectively (Auld et al. 2017). The adoption of AVs/CAVs could lead to network-wide impacts on VKT, VHT, speed, and delay.

In summary, the findings from the literature suggest that the adoption of both private and shared AVs/CAVs could lead to network-wide impacts on VKT, VHT, speed, and delay, depending on the assumed MPR, highway capacity changes, and other related assumptions (Zhao and Kockelman 2018; Kockelman et al. 2017; Kim et al. 2015; Auld et al. 2017). Only a few studies investigated scenarios with private AVs/CAVs assuming no availability of shared AVs/CAVs (Auld et al. 2017; Kockelman et al. 2017; Kim et al. 2015). Those studies found that private AVs/CAVs could lead to a 19%-271% increase in VKT, a 12%-180% increase in VHT, and a 9%-33% reduction in average travel speed (Auld et al. 2017; Kockelman et al. 2017; Kim et al. 2015). On the other hand, a widespread adoption of shared AVs was found to lead to a maximum of 35% reduction in VMT, 41% reduction in VHT, and 8% increase in average speed (Childress et al. 2015). This paper contributes to the limited number of studies that evaluated scenarios with only private (and no shared) AVs or CAVs to provide clarity on the network-level changes in the case where shared AVs or CAVs are not embraced by public agencies and communities in the future and private AVs



and CAVs dominate the market.

In the majority of previous studies, the substantial improvements in highway capacity, which were assumed due to AV and CAV technologies, were found to offset the adverse impacts of increased VKT. However, such capacity improvements may not be up to the standards community.

The impact of AVs and CAVs on capacity has been studied both from a theoretical perspective (using fundamental equations of motion to derive acceleration/deceleration, speed, and spacing for the vehicles of interest) as well as through simulation analysis. Capacity findings related to the introduction of AVs into the traffic stream are mixed, with many studies reporting improvement (Chang and Lai 1997; Minderhoud and Bovy 1999; Tientrakool et al. 2011; Vander Werf et al. 2002) while others reporting degradation (Bierstedt et al. 2014; Adebisi et al. 2020). The literature that showed promising gains in capacity due to the introduction of AVs reported inconsistent levels of improvements for the same MPR across studies. Multiple factors impact freeway segment capacity estimation, including the time gap, platooning, car following model, and desired speed. Most of the literature reporting gains in capacity have used "aggressive" AV parameter assumptions that result in capacity enhancements. Considering factors such as maturity and reliability of the associated technologies, liability aversion, and eminence, original equipment manufacturers (OEMs) are likely to introduce AVs with decision algorithms that on average will be more conservative compared to human drivers, with a focus on crash avoidance. Such decision algorithms are therefore likely to have negative implications on roadway capacity. In this study, when simulating AVs, the authors make assumptions that reflect such conservative decision algorithms, in line with some of the recent studies on the impact of AVs on freeway capacity (Adebisi et al. 2020; Bierstedt et al. 2014).

On the other hand, the literature on the impact of CAVs revealed significant improvements in traffic stream capacity (Ni et al. 2010; Shladover et al. 2012; Tientrakool et al. 2011; VanderWerf et al. 2001; Vander Werf et al. 2002), which is directly related to the share of these vehicles present in the stream. The estimated improvements differ across studies with gains reported between 50%- 270% for a fully saturated (100% CAV) traffic stream. This study introduces capacity adjustments based on detailed simulation analysis which accounts for the micro-level interactions among AVs, CAVs, and traditional human-driven vehicles in access-controlled roadway facilities (freeways and highways). This method is expected to provide more realistic capacity estimates under various market shares of personal AVs and CAVs, compared to past research because the car following rules vary according to the attributes of each lead and following vehicle pair in the simulation. In addition, some of the previous studies did not account for the additional demand from new traveler groups that might be accompanied with the adoption of autonomous and connected vehicle technologies (Zhao and Kockelman 2018; Auld et al. 2017; Childress et al. 2015). This study assumes that the availability of self-driving vehicles will induce demand for travel from younger and older adults for some trip purposes, such as shopping and home-based non-work trips.

1.3 Triangle Regional Model

This analysis focuses on major parts of the Raleigh-Durham-Chapel Hill combined metropolitan statistical area (CSA), which is the second largest CSA in North Carolina with a total population of 2,238,315. This area is also known as the Triangle Region, thanks to having three main employment centers (the cities of Raleigh, Durham, and Chapel Hill) within a 20 to 30-minute drive from each other. Geographical boundary of this study is defined by the boundary of the Triangle Regional Model (TRM), an aggregated trip-based model for the Triangle Region with four major steps: trip generation, trip distribution, mode choice, and trip assignment. The model covers an area of 3380 square miles with the entire areas of Orange, Wake and Durham counties, and parts of Chatham, Person, Granville, Franklin, Nash, Johnston, and Harnett Counties in NC. The entire region is divided into 2857 traffic analysis zones (TAZ). Version 6 of the model (named TRMv6), which is used in this study, includes several updates on facility capacities based on the 2010 Highway Capacity Manual and improved delay estimation for signalized intersections. Figure 1.1 shows the county boundaries and TAZs of TRMv6.

The model utilizes a socioeconomic database of the region which includes the total number of households, median household income, land-use characteristics, employment, and other sociodemographic information for each of the 2857 internal TAZs. TRMv6 is calibrated to represent the regional socioeconomic conditions for 2013 (base year) with total household population of 1,685,832, and designed to model future scenarios up to 2045 (design year) with predicted house- hold population of 2,963,818. For future year analyses, the socioeconomic inputs are generated by the software CommunityViz 2.0

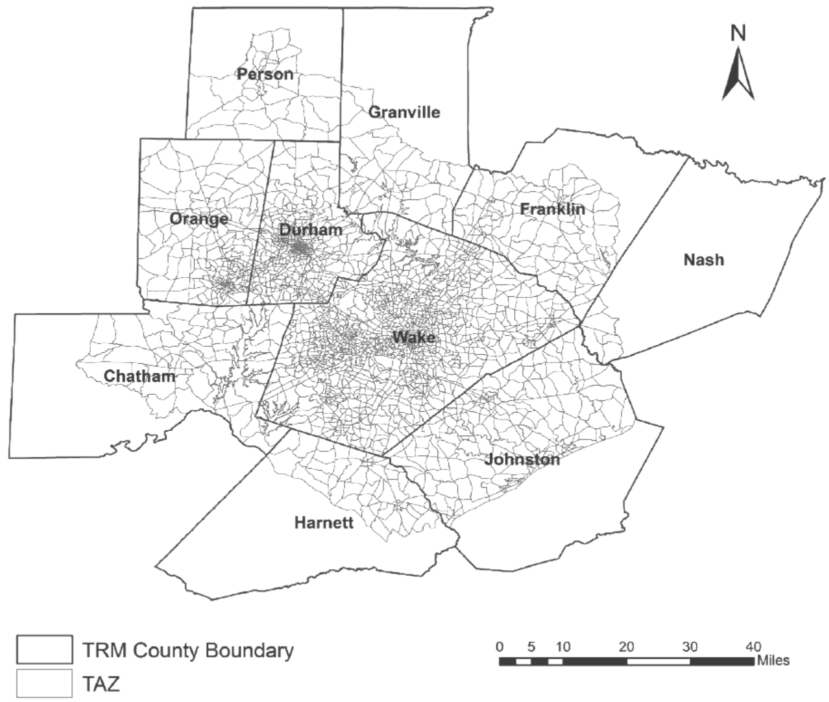


Fig. 1.1 Triangle Regional Model area. (Data from TRM 2016.)

(Com 2020), which projects the future growth given the current development pattern and assumptions on the attractiveness of different zones. This study uses the 2045 socioeconomic database and highway network file for modeling AV and CAV scenarios.

At the trip generation step, the TRM uses a multinomial logit (MNL) model to estimate the number of trips produced in a typical weekday for three user types (working adults, non-working adults, and children) and for six trip purposes: home-based work (HBW), home-based shopping (HBShop), home-based K12 school (HBK12), home-based other (HBO), non-home non-work (NHNW), and work-based non-home (WBNH). The MNL model was initially estimated based on data from regional household surveys and on-board transit surveys. The five socioeconomic strata used in the TRMv6 (with percentage of total households in brackets) are

- Strata 1 [9.3%]: Households with no vehicles (all income levels
- Strata 2 [15.2%]: Low-income households (annual household income lower than $25,000)
- Strata 3 [2.4%]: Medium-income households (annual household income between $25,000 and $75,000) with at least one vehicle but fewer vehicles than workers
- Strata 4 [45%]: Medium-income households (annual household income between $25,000 and $75,000) with as many or more vehicles than workers
- Strata 5 [28.1%]: High-income households (annual household income over $75,000) with vehicles

Trip attraction is modeled using linear regression where the number of attractions depends on population, employment, or enrolled K12 students as appropriate to the trip purpose.

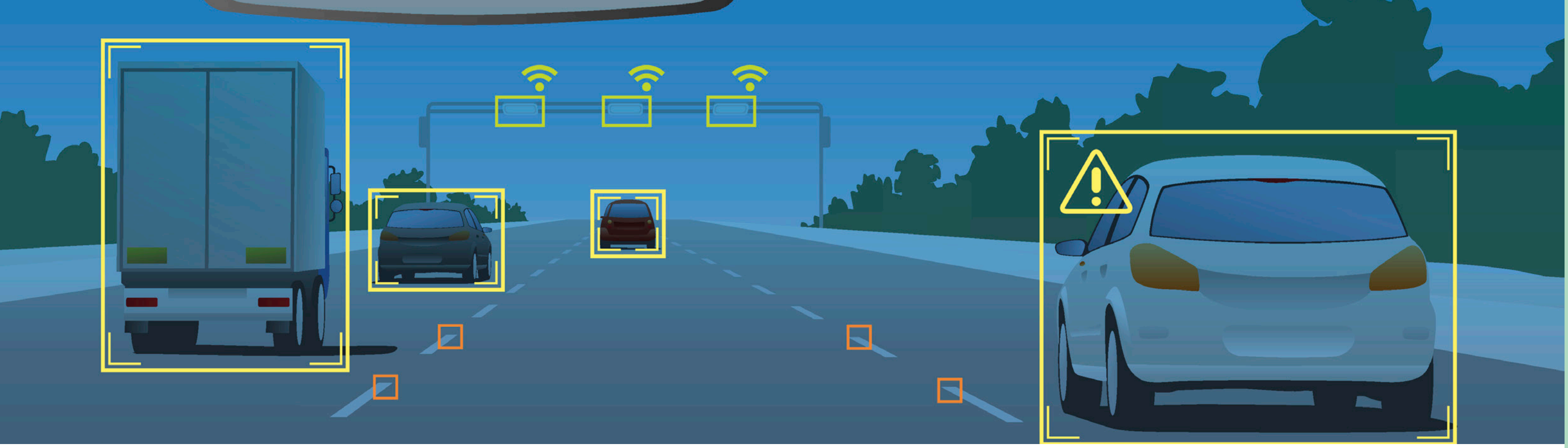
The TRM model considers four major time periods: AM peak (6:00-10:00am), PM peak (3:30- 7:30pm), mid-day (10:00am-3:30pm), and nighttime (7:30 pm - 6:00 am). The AM and PM peak periods are subdivided into three sub-periods: (i) shoulder 1 (6:30-7:30am for AM, 3:30-5:00pm for PM), (ii) peak (7:30-8:30 am for AM peak, 5-6 pm for PM peak), and (iii) shoulder 2 (8:30- 10:00am for AM peak, 6-7:30 pm for PM peak). The generated trips are distributed among peak and off-peak periods based on factors representing travel behavior in the region in 2010 (original factors were obtained from the 2006 Triangle household survey and were later re-weighted to 2010)

Trip distribution is based on destination choice models for each household stratum and for each of the six trip purposes. These models predict the probability that trips for each stratum from a home TAZ will be attracted to another TAZ based on the attributes of the TAZ and cost of travel. Travel times and mode-choice logsum values are used as the primary travel impedance in the destination choice models.

Before the mode choice decision, TRMv6 uses a binary non-motorized mode split model to estimate the number of trips by motorized and non-motorized modes. There are twelve mode choice models with one for each trip purpose and each time period (peak and off-peak). The models use a nested logit form with three nested levels. The first level of the nested logit gives the choice probability between auto and transit modes. For the auto mode, the second level provides three more options: drive alone, carpool, and auto-intercept (long auto trips that combine a car trip to a park and ride facility close to the destination, and a short transit shuttle leg to the final destination). The third level for the auto mode estimates the probability of carpool trips having two or more than three individuals traveling together. For transit trips, the second level calculates the probability of transit trips using local bus transit, express bus transit, or urban rail. The third nest level for transit calculates the probability of walking to transit, drive to park-and-ride lots to transit, or being dropped off at a transit stop.

Traffic assignment is conducted in two parts: highway traffic assignment and transit trip assignment. Highway traffic assignment uses a multimodal multiclass user equilibrium method to assign the origin-destination pairs to different roadway segments by time period and for four classes of vehicles: single-occupant vehicles (SOV), high-occupancy vehicles (HOV), single-unit trucks (SUT), and multi-unit trucks (MUT). Transit assignment uses the TransCAD pathfinder transit assignment procedure to load the peak and off-peak transit-trip production-attraction matrices onto the peak and off-peak transit-route systems, respectively. The assignment is done separately for nine combinations of three transit modes (local bus, express bus, and rail) and three access modes (walk-access, park-and-ride, and kiss-and-ride).

The model uses an iterative feedback mechanism, which loops through the destination choices, non-motorized trip splits, mode choices, and assignments to ensure that the model uses consistent travel costs between input and output for the peak period.



1.4 Methodology

This study makes modifications to the trip generation, mode choice, and traffic assignment sections of the Triangle Regional Model to simulate the impacts of privately-owned AV and CAV adoption in the year 2045. Specifically, induced transport demand from younger and older adults in households that own private AVs/CAVs is introduced in the trip generation step. In addition, the TRM mode choice model is modified to account for changes in the perceived in-vehicle travel time for AV and CAV trips and to simulate different levels of market penetration of AVs and CAVs. Last, the capacity of the uninterrupted flow facilities operating without any traffic controls in the TRM transportation network (freeways, and multi-lane and two-lane highways) is adjusted to simulate the impacts of AVs and CAVs in the traffic stream.

Figure 1.2 presents a graphical summary of the study methodology. The modifications introduced in the TRM model, which are based on microsimulation analysis and assumptions from the literature, are explained in further detail in the following sections.

Vehicle Automation and Connectivity

This study analyses the impacts of future adoption of Society of Automotive Engineers (SAE) Level 4 and Level 5 AVs (Society of Automotive Engineers 2018). Level 4 AVs are defined as driverless vehicles that can operate within specific geographical boundaries or under specific traffic conditions, while Level 5 AVs can operate as driverless vehicles in all locations and traffic conditions (Society of Automotive Engineers 2018). This study assumes that individuals may have access to Level 4 and Level 5 AVs by 2045. It is also assumed that some trips within our study area could be completed, from start to end, by Level 4 AVs while all trips could be completed by Level 5 AVs. However, trips for Level 4 and 5 AVs are not modeled separately in this chapter.

AVs are assumed to be able to assess their surroundings by tracking other vehicles and infrastructure (signals, signs, markings and other displayed information about traffic and roadway) in their vicinity, and safely navigate through the prevailing roadway conditions. In addition to these characteristics, CAVs can communicate with other

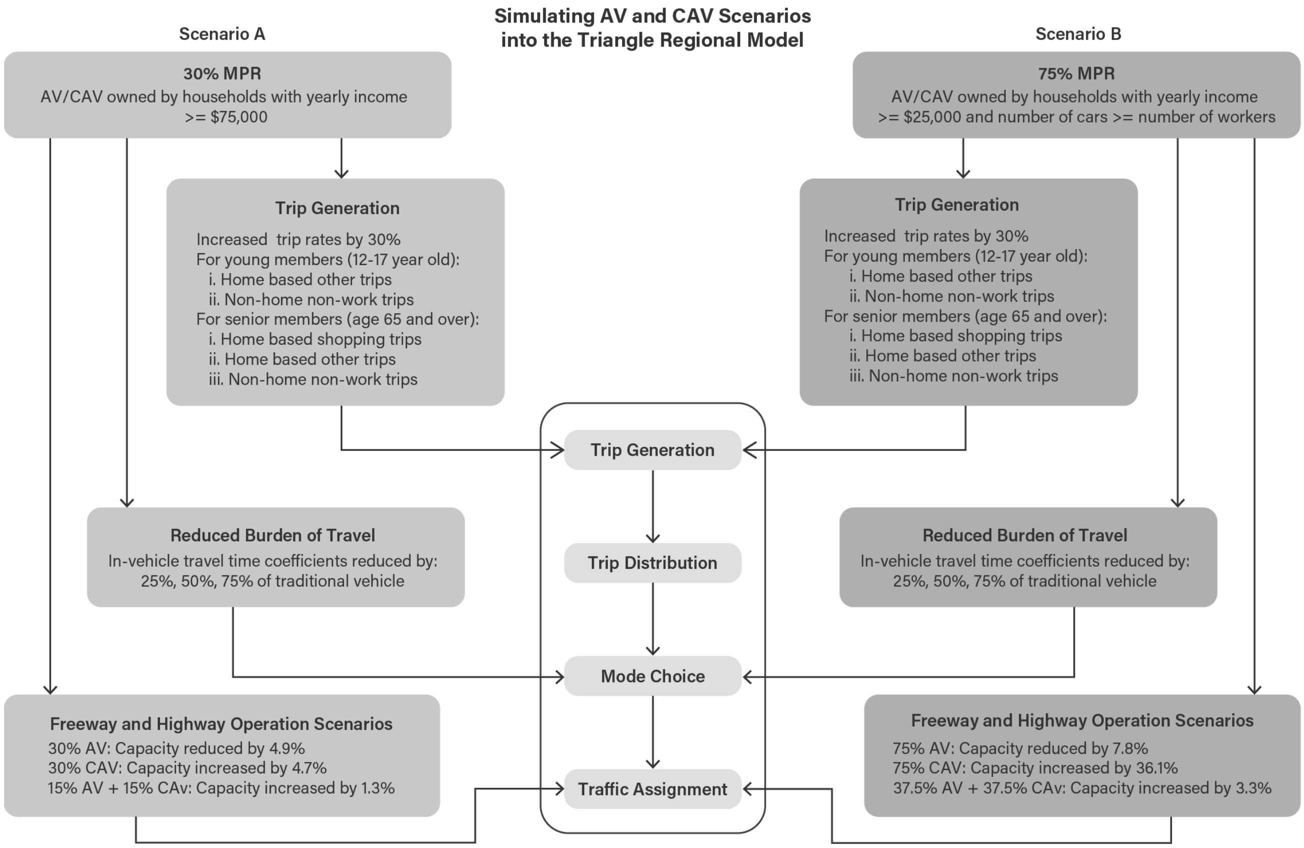


Fig. 1.2 AV and CAV scenarios in the Triangle Regional Model.

CAVs and infrastructure to have a much better understanding of the traffic stream and network's operating condition. This communication enables CAVs to operate more safely and efficiently than AVs. In this study, these distinctive characteristics of AVs and CAVs are reflected through the microsimulation study, the outputs from which are used to adjust the capacity of freeways and highways. Both AVs and CAVs are assumed to operate under a fully driverless mode, which enables more productive use of the riders' in-vehicle travel time.

Market Penetration and Emerging Vehicle Technologies

Autonomous and connected vehicle technologies are likely to be adopted gradually over a significant period of time (Litman 2018). Existing four-step travel demand models typically do not include the option to use AVs or CAVs for travel in the mode choice step, although this will probably change in the near future as these models are updated. Data from a stated preference survey in the Triangle Region that include scenarios related to AV and CAV adoption are needed in order to appropriately modify the existing mode choice model within the TRM and include the option of an AV or CAV for each trip purpose. Since such data are not currently available, an alternative approach is undertaken to simulate the penetration of emerging vehicle technologies in the Triangle Region.

Litman (2018) predicted the MPR for autonomous and connected vehicles based on the timeline of the adoption of past technologies and concluded that by 2040 and 2050, autonomous and connected vehicle sales will reach 40%-60% and 80%-100% respectively, while travel by these vehicles will reach to 30%-50% and 50%-80% of total personal vehicle travel, respectively. In addition, studies have shown that early adopters of emerging vehicle technologies tend to be households with high income and more than one personal vehicle (Hjorthol 2013; Petersen

et al. 2006). Based on these findings from the literature, two main scenarios are considered with respect to the market penetration of AVs and CAVs in 2045. In Scenario A (conservative scenario), only high-income households in the Triangle Region are assumed to own personal AVs or CAVs. Given the percentage of households with vehicles belonging to the high-income category (TRM socioeconomic strata 5), Scenario A translates into an approximately 30% MPR of AVs and CAVs in 2045. Within Scenario A, three sub-scenarios are considered (30% AV; 30% CAV; 15% AV and 15% CAV) to differentiate between the impacts of AVs and CAVs in the analysis. Scenario B aims at simulating an optimistic scenario with the high-income and medium-income households with as many or more vehicles than workers (TRM socioeconomic strata 4 and 5) owning AVs or CAVs in 2045. Scenario B would result in an approximately 75% MPR of AVs and CAVs, and three related sub-scenarios (75% AV; 75% CAV; 37.5% AV and 37.5% CAV).

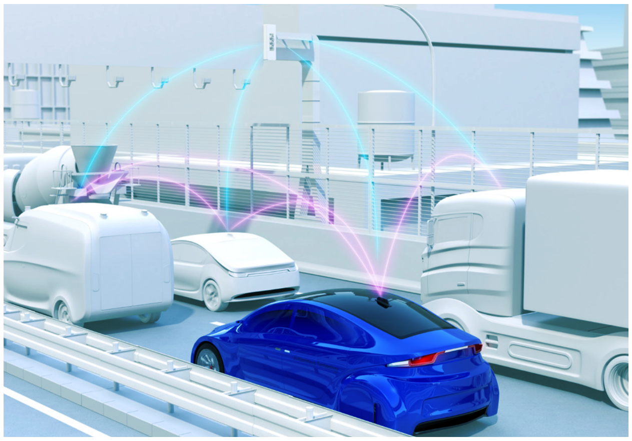
Highway Capacity

The impact of AVs and CAVs on the capacity of traffic stream was assessed using state-of-the- art longitudinal and lateral behavior models introduced into SUMO – an open source simulation platform (Lopez et al. 2018) . Detailed information on the models, parameter values, and results of the simulation analysis are discussed in Samandar et al. (2020), and a summary is provided in this section.

Relying on their on-board sensors to monitor their immediate environment, AVs have continuous access to data from their surroundings. This capability enables AVs to track other vehicles in their vicinity, but also to instantaneously cope with the changes in the driving and environmental conditions of the traffic stream. Sensing and mechanical delays, therefore, make up the reaction time of these vehicle types. The acceleration framework developed by Xiao et al. (2017) and Milanés and Shladover (2014) was considered optimal for representing the longitudinal behavior of AVs. This integrated longitudinal behavior model has three distinctive modes of cruising, car-following, and approaching or gap-closing.

CAVs rely on their on-board communication and sensing instruments to gather information about their surroundings. Critical driving decisions are constantly made on the bases of line- of-sight and intercepted signals from other connected vehicles or the infrastructure. Presence of communication capability enables CAVs to be confident of the movements of other connected vehicles in their vicinity, changes in downstream traffic conditions, and thus, instantaneously react to the change in movements of surrounding vehicles or the traffic conditions. Furthermore, CAVs are assumed to communicate with each other and form platoons with short following time gaps. Mechanical delay and communication latency are the two components of reaction time for CAVs. Considering the capability of CAVs to be aware of the movements of nearby vehicles and the condition of the driving environment, a deterministic acceleration modeling approach best represents the movement of these vehicles portrayed by the works of Milanés and Shladover (2014), Xiao et al. (2017), and Xiao et al. (2018).

Contrary to previous related simulation studies, this analysis captures the interaction of AVs, CAVs, and TVs in mixed-traffic conditions. This is accomplished through longitudinal behavior models and other vehicle characteristics that depend on the type and operations of the simulated vehicles. From a longitudinal perspective, we have implemented a dynamic car-following model for CAVs that employs different strategies based on the type of vehicle being followed. The model implements CAV parameters (e.g., short time gaps and platooning) if the vehicle being followed is another CAV. If the vehicle being followed does not have communication capabilities (i.e. AVs and TVs), the CAV relies on onboard sensors and its movement shifts to an AV car-following mode (conservative time gaps and no platooning). The longitudinal behavior of TVs and AVs, however, do not depend on the type of vehicles being followed (i.e. they have vehicle-independent car-following models). There are several other differences between the three vehicle types simulated including, but not limited to, minimum time gap, platoon formation, desired speed, cooperative lane changing, and distinctive car-following algorithms. Equipped with both vehicle-to-vehicle communication and onboard sensors that constantly track the environment, CAVs are able to maintain short time gaps between alike vehicle types. The other two classes of vehicles (AVs and TVs), however, do not have the same capabilities and as such have conservative time gaps. Similarly, the presence



of communication among CAVs allows them to form and maintain platoons with relatively small headways, whereas AVs and TVs are not able to do so due to lack of communication. The tendency of vehicles to follow the speed limit is portrayed by the desired speed limit in the micro-simulation. Our simulation assumes that AVs and CAVs will abide by the speed limit and thus will have a fixed desired speed, whereas TVs will follow a stochastic, field calibrated desired speed distribution as in most current simulation models.

Findings from our simulation reflect changes in capacity for freeways and highway segments operating without interruptions. Results indicate that the introduction of AVs to the traffic stream will result in degradation of capacity, and that is directly related to the amount of interaction between AVs and traditional vehicles, and the safety time gap that such vehicles strive to maintain. Several factors such as maturity and reliability of associated technologies, liability aversion, and eminence have lead OEMs (original equipment manufacturers) to introduce AVs with decision algorithms that on average are more conservative compared to human drivers. Such decision algorithms have negative implications on roadway capacity. However, CAVs are found to improve capacity at all levels of market penetration, with the greatest improvement (90% increase compared to baseline capacity) happening at 100% MPR of CAVs. These findings have important implications for the AV and CAV scenarios assumed in this study. Assuming that only AVs penetrate the market by 2045, highway capacity is expected to decrease by 4.9% for 30% MPR and 7.8% for 75% MPR based on the findings of the simulation analysis. On the other hand, the scenarios that focus on the adoption of CAVs are associated with a 4.7% increase in capacity for 30% MPR and a 36.1% increase for 75% MPR. Last, for the scenarios that assume a 50-50 mix of AVs and CAVs in the MPR, the interactions between AVs, CAVs, and traditional vehicles in the traffic stream will lead to a small improvement in capacity even for high MPR (1.3% increase for 30% MPR and 3.3% increase for 75% MPR). These capacity changes are implemented on the freeways and highway segments operating without traffic signals or intersections.

Induced Travel

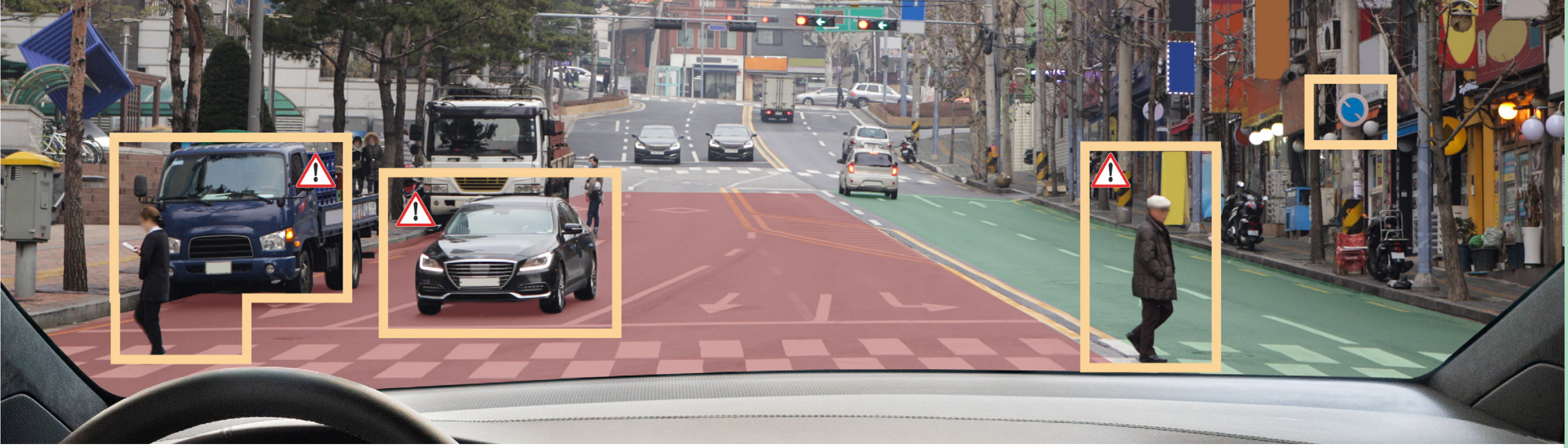
Autonomous and connected vehicles are expected to increase accessibility and offer new mobility options for current non-drivers, senior citizens, and individuals with disabilities. Therefore, it is expected that in the future, additional trips will be generated from people who are currently too young to have a driver's license and people who have difficulty driving, including elderly and disabled individuals (Truong et al. 2017; Wadud et al. 2016; Sivak and Schoettle 2015; Harper et al. 2016). A recently passed House Bill (HB 469) in North Carolina exempts AV/CAV operators from the requirement to hold a driver's license (NC General Assembly 2017). In addition, HB 469 states that an adult is required if a person under 12 years old is in an AV/CAV (NC General Assembly 2017). Therefore, given the current legislation, new trips could be generated in the future by people as young as 12 years old. A few studies have incorporated induced demand in their analysis based on rough estimates. For instance, Kockelman et al. (2017) introduced a 20-100% increase in trip generation rates for all trip purposes and for all higher-income households. Nair et al. (2018) introduced a 5% induced trip production factor attributed to the possible availability of ride-hailing services. This study assumes increased trip rates only for individuals in age groups 12-17 and 65+ who belong to households with AVs or CAVs, following the recommendations of Wadud et al. (2016) and Truong et al. (2017). In a detailed study, Wadud et al. (2016) demonstrated the gap between travel demand and travel options for different age groups based on 2009 National Household Travel Survey data. The study suggested that the declining travel rate between the age 44 and 62 represents the natural rate of decline because travel needs gradually decrease with increasing age. In addition, the authors argued that the higher rate of decline after the age of 62 could be due to impaired driving abilities (Wadud et al. 2016). Wadud et al. (2016) also suggested that AVs could generate additional vehicle kilometers traveled (VKT) from the current non-drivers who are not allowed to have a driver's license. Similar travel trends are found by Truong et al. (2017) based on 2007-2010 data of the Victorian Integrated Survey of Travel and Activity. Along with the elderly population group, Truong et al. (2017) emphasized on the possible travel gap created for the 12-17 year old age group who are currently dependent on public transport or their parents to meet their travel needs. In the future, such needs have the potential to be filled by AVs (Truong et al. 2017). Based on these findings, we introduce a 30% increase in trip rates for the individuals between 12 and 17 years old and individuals who are 65 years old or older. Increase in the trip rates for these individuals is implemented for certain trip purposes (HBO, NHNW, HBShop) and only for the households who are assumed to own AVs or CAVs based on Scenarios A and B. Specifically, a 30% increase in the trip rate for HBO, NHNW, and HBShop purposes is assumed for individuals who are 65 years old or older, and for HBShop and NHNW purposes for individuals between 12 to 17 years old. The TRM does not provide any information on individuals with disabilities and therefore additional trips from this population group could not be incorporated into this analysis. For the population between 18 to 64 years of age who already has full access to personal vehicles, it is assumed that their travel needs are already met with or without automation and connectivity (Wadud et al. 2016; Truong et al. 2017) and therefore, their trip rates remain unchanged.

In-Vehicle Travel Time

It is expected that people driving in Level 4 or 5 AVs or CAVs will feel less burdened and may also be able to perform other functions, such as reading, working, or sleeping, which would result in a significant reduction in the perceived value of time (VOT) (Singleton 2019). Previous studies have made substantial reductions in the in-vehicle travel time (IVTT) coefficient for autos in the mode choice step of travel demand models to account for the change in VOT (Gucwa 2014; Kim et al. 2015; Zhao and Kockelman 2018). For example, Kim et al. (2015) reduced the IVTT coefficients for autos by 50% in the activity-based model for Atlanta to simulate AV. However, survey results have shown that very few of the respondents are comfortable with using the in-vehicle travel time for working (Schoettle and Sivak 2014a), and some researchers have argued that more modest VOT reductions should be analyzed in future studies (Singleton 2019). This research examines the sensitivity of the network-level performance characteristics for a range of VOT changes, by testing a 25%, 50%, and 75% reduction in the IVTT coefficient for households who are assumed to own AVs or CAVs under Scenarios A and B.

Summary of Findings

- People will make more and longer trips by personal vehicles with increasing market share of personal AVs and CAVs.
- High market share of personal AVs deteriorates the performance of the network, leading to a 4% reduction in peak-period travel speed.
- High market share of personal CAVs improves network performance, resulting in 7.6% increase in peak-period travel speed and 8% reduction in daily hours of delay.



1.5 Results and Discussion

The TRM base scenario provides the baseline results on system performance considering zero AV or CAV adoption for the year 2045. The model was subsequently run for a number of scenarios on AV and CAV market penetration and related highway capacity changes, assuming induced demand and reduced burden of travel for AV and CAV adopters. The results are presented in two sections. The first section focuses on the regional impacts of different market penetration scenarios for AVs and CAVs in 2045. For a given MPR of AVs and CAVs, highway capacity is adjusted based on the results of the microsimulation analysis. For all scenarios, the IVTT coefficient (representing the burden of in-vehicle travel) is reduced to 50% of the traditional vehicles. The second section includes a sensitivity analysis for IVTT and explores how changing the impact of travel time on an individual's utility may lead to differential outcomes for the transportation network.

Regional Impacts of Personal AV and CAV Adoption

Table 1.1 presents the daily vehicle kilometers traveled (VKT), daily vehicle-hours traveled (VHT), average peak-period travel speed on freeways, daily hours of delay, and average travel time to work in the Triangle Region for six scenarios of AV and CAV adoption and compares them with the 2045 base scenario. The first three scenarios (A1, A2, A3) are based on Scenario A and assume a total of 30% MPR but differ in terms of the rate of personal AV and CAV, as shown in Table 1.1. Similarly, the next three scenarios (B1, B2, B3) are based on Scenario B and assume a total of 75% MPR. Each scenario is associated with a change in capacity for freeways and two-lane and multi-lane highway segments operating without traffic signals or intersections, as can be seen in Table 1.1. In addition, Figure 1.3 graphically presents the percentage change of daily VKT, daily VHT, average peak-period freeway speed, and daily delay for the six scenarios in comparison to the base scenario.

The results indicate that VKT increases with increasing market penetration of privately-owned AVs and CAVs. The estimated changes range between 1.2% and 3.6% increase in VKT, with the highest change corresponding to the scenario with the highest market penetration of

Table 1. Network-level impacts of AV and CAV adoption

Market penetration rate scenarios	%Change in capacity	Vehicle-kilometers traveled Value	Vehicle-kilometers traveled %Change	Vehicle-hours traveled Value	Vehicle-hours traveled %Change	Peak-period freeway speed Value (km/h)	Peak-period freeway speed %Change	Hours of delay Value	Hours of delay %Change	Travel time to work Value (min)	Travel time to work %Change
Base scenario	0%	146,119,950	-	2,544,539	-	84.81	-	451,335	-	25.84	-
(A1) 30% AV	-4.90%	147,823,562	1.17%	2,613,617	2.71%	82.88	-2.28%	490,561	8.69%	26.37	2.05%
(A2) 30% CAV	4.70%	148,317,054	1.50%	2,577,796	1.31%	85.62	0.95%	455,626	0.95%	25.98	0.54%
(A3) 15% AV, 15% CAV	1.30%	148,198,047	1.42%	2,590,648	1.81%	84.65	-0.19%	467,688	3.62%	26.13	1.12%
(B1) 75% AV	-7.80	149,594,128	2.38%	2,681,339	5.38%	81.43	-3.98%	528,782	17.16%	26.93	4.22%
(B2) 75% CAV	36.10%	151,437,787	3.64%	2,567,783	0.91%	91.25	7.59%	415,156	-8.02%	25.52	-1.24%
(B3) 37.5% AV, 37.5% CAV	3.30%	150,079,662	2.71%	2,632,369	3.45%	84.81	0.00%	482,754	6.96%	26.31	1.82%

CAVs, due to the additional capacity introduced to the system. For the same MPR of total AVs and CAVs, the daily VHT and daily delay decrease as capacity improves.

The largest increase in VHT and daily delay is observed for 75% MPR of AVs (scenario B1). Specifically, the daily VHT and daily delay increase by 5.4% and 17.2%, respectively, and the peak-period freeway speed decreases by 4%, due to the combined effect of capacity reduction caused by AV traffic operations and induced demand from new user groups. An 8% reduction in daily delay and a 7.6% increase in peak-period freeway speed are found for 75% CAVs (scenario B2). The assumed 50% reduction in IVTT coefficients compared to the traditional vehicles for AV and CAV adopters also leads to changes in mode choice and distance travelled, resulting in increasing VKT and VHT. Overall, the changes estimated for daily VKT, daily VHT, and average travel time to work are relatively small and below 5%. The same holds for average peak-period freeway speed, except for the 75% CAV scenario which leads to a 7.6% increase in peak-hour speed. On the other hand, the changes in hours of delay are more significant, ranging between 1% and 17%. We note that the total hours of delay increase even for some of the CAV scenarios for a number of reasons. First, capacity improvements due to CAVs are mainly realized in freeways and non-signalized highway segments

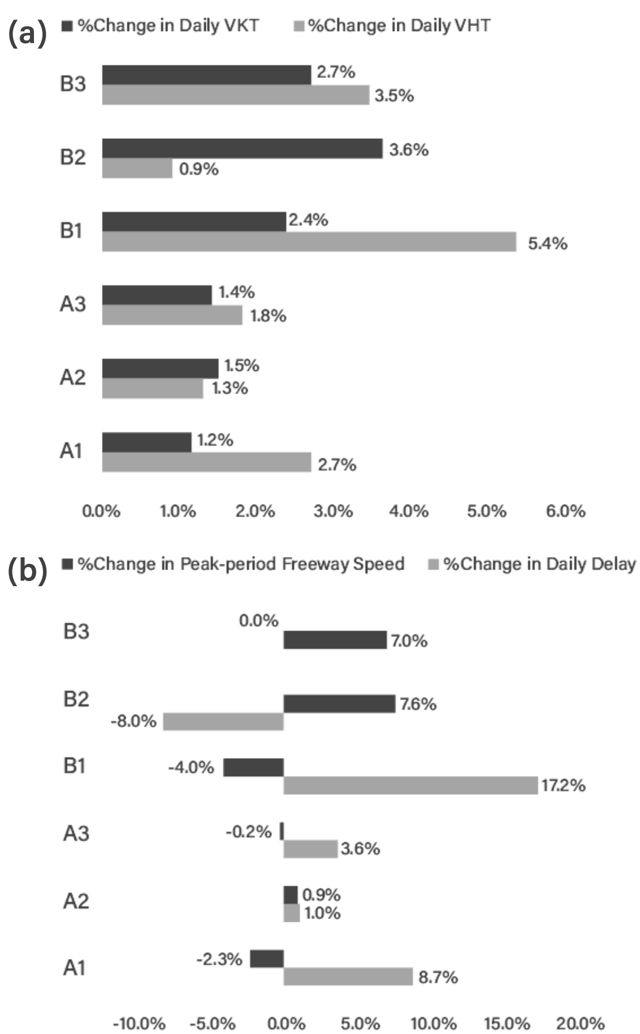


Fig. 1.3 Impact of AV and CAV adoption on transportation network demand and performance: (a) percentage change in daily VKT and daily VHT compared to the base scenario; and (b) percentage change in peak period freeway speed and daily delay compared to the base scenario.

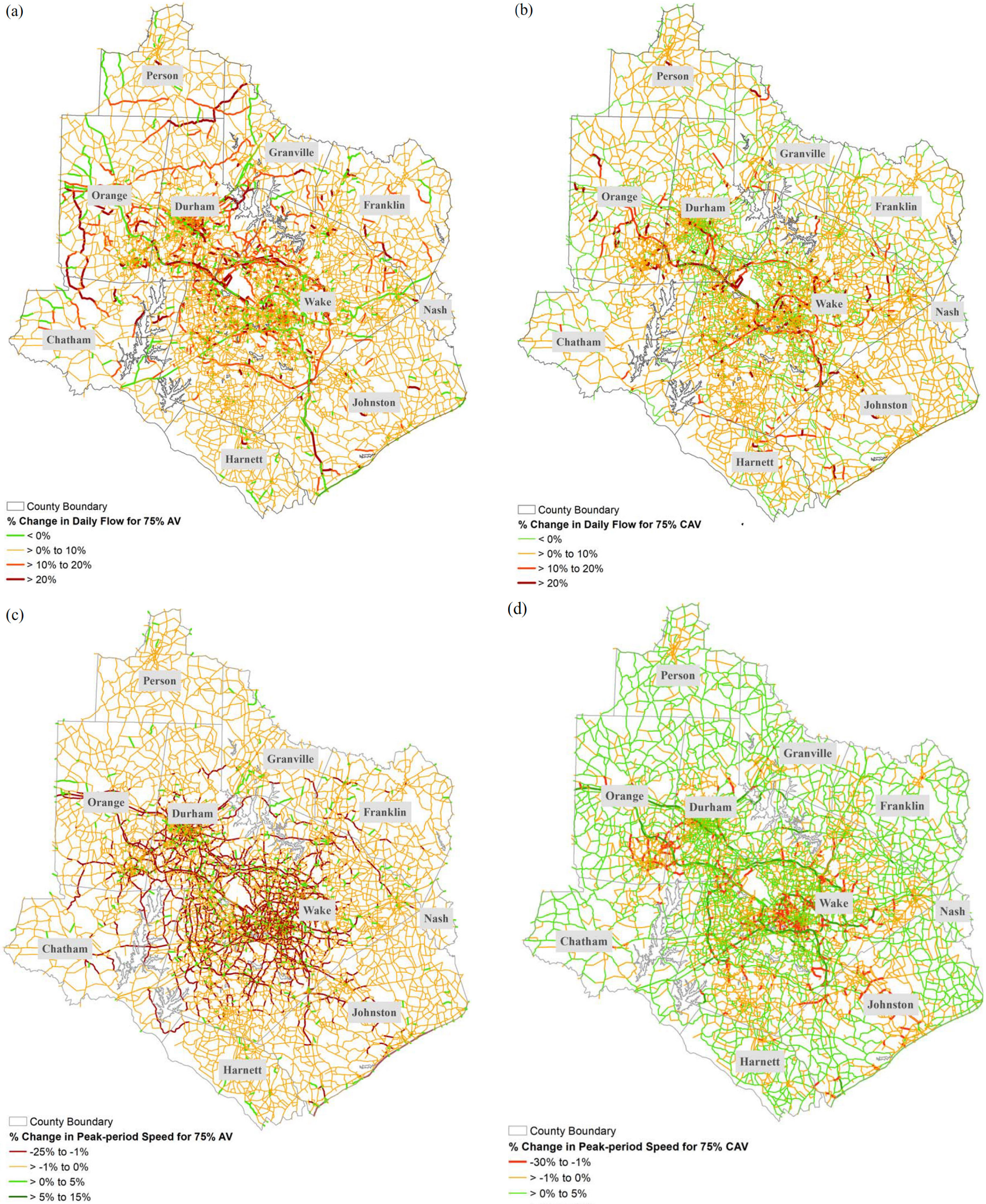


Fig. 1.4 Link flow and peak-period link speed changes in the Triangle Region's network for AV and CAV adoption scenarios: (a) percentage change in link flows for 75% MPR of AV; (b) percentage change in link flows for 75% MPR of CAV; (c) percentage change in peak period link speed for 75% MPR of AV; and (d) percentage change in peak-period link speed for 75% MPR of CAV.

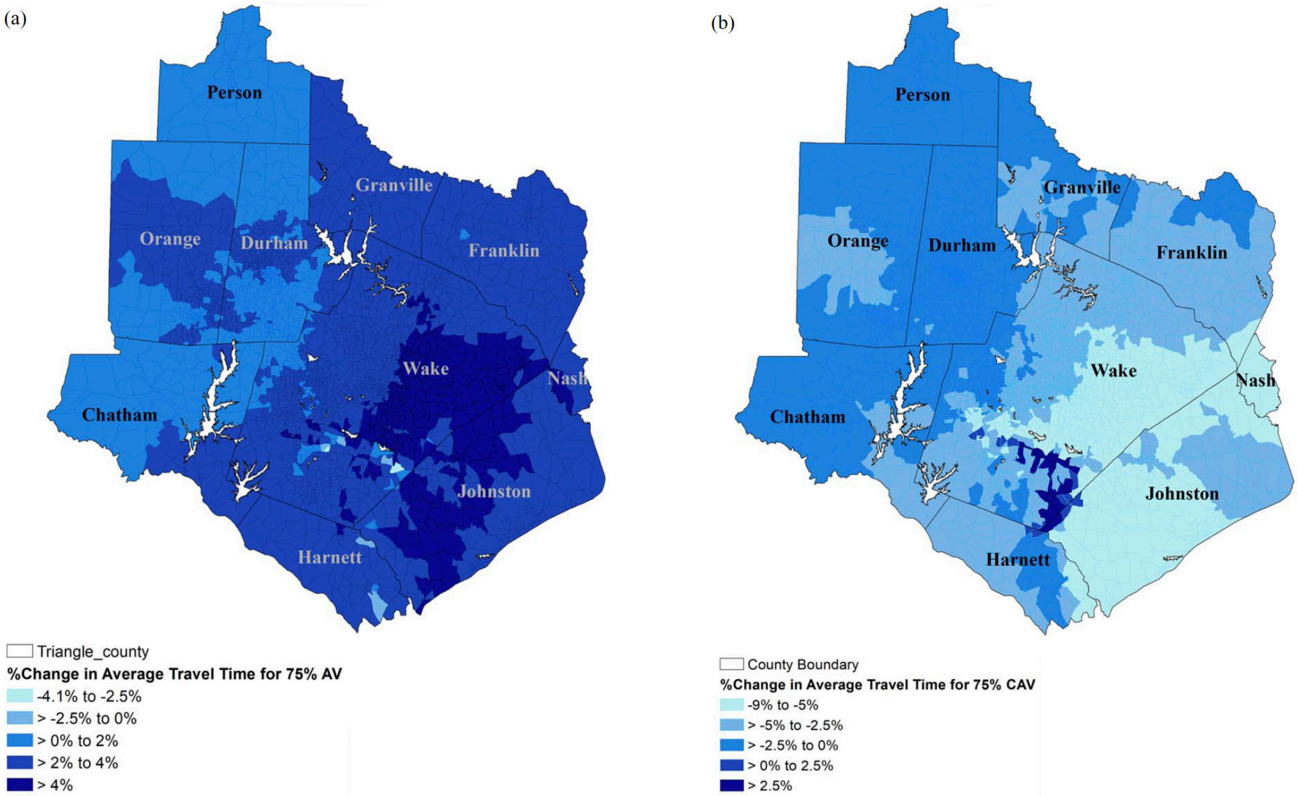


Fig. 1.5 Changes in average travel time during the peak periods for all trips by origin zone in the Triangle Region for AV and CAV adoption scenarios; (a) Percentage change in average travel time for all trips by origin for 75% MPR of AV; and (b) Percentage change in average travel time for all trips by origin for 75% MPR of CAV.

and they do not benefit the rest of the network. Second, increased trip rates affect the total vehicle kilometer traveled (VKT) and could lead to higher delays in some parts of the network. In general, the results indicate that 30% MPR of CAVs will result in network performance similar to the baseline scenario (0% MPR of AVs or CAVs), while 75% MPR of AVs is found to lead to significant deterioration of the network performance.

Besides the results on aggregate network performance indicators, a number of figures are presented herein to provide insights on the spatial distribution of the estimated effects in the Triangle Region's transportation and activity system. Figure 1.4 shows the change in the daily link flows and peak period link speeds in the transportation network for 75% MPR of AVs and 75% MPR of CAVs, in comparison to the base scenario.

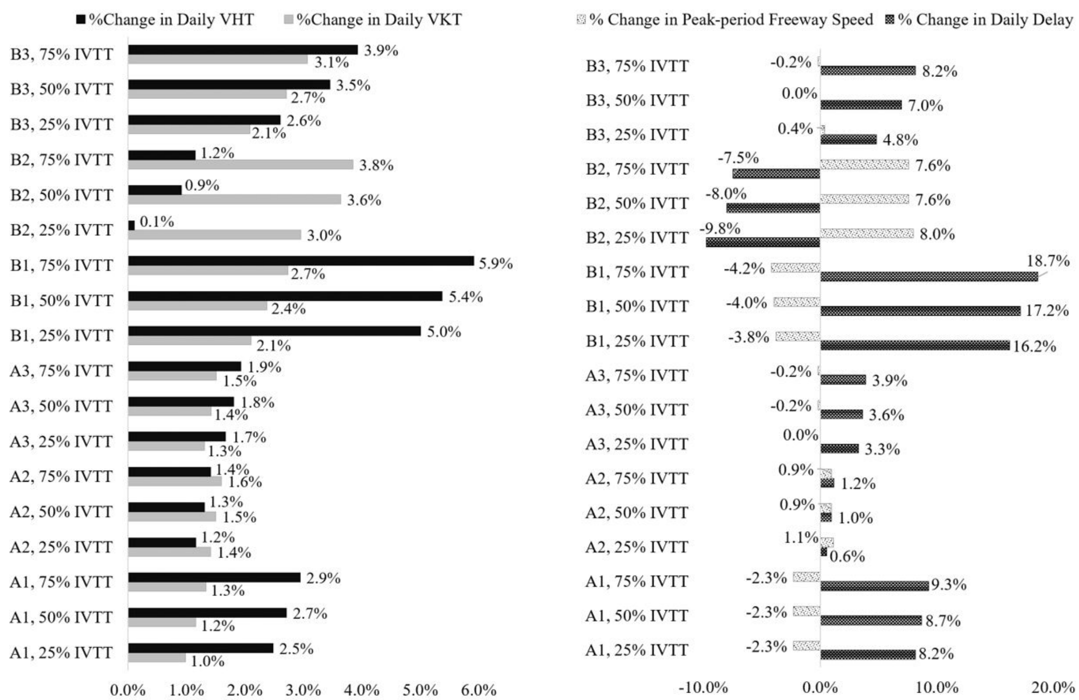
As seen in Figures 1.4(a) and 1.4 (b), a higher amount of daily vehicle flow and lower speeds during the peak period due to 75% MPR of AVs are clustered around the City of Raleigh located in Wake County, and the City of Durham located in Durham County. The freeway links in both the scenarios have higher volume of traffic compared to other facility types. For 75% MPR of CAVs, the improved capacity attracts more traffic into the freeway and highway links, which reduces the demand on arterial and collector roads. Significant improvements are also found for peak-period speed on freeways. Although freeway and highway links show greater improvements in peak-hour speed, positive impacts are also found on most of the arterial links and some of the local roads. For 75% MPR of AVs, most of the network experiences reductions in peak-period speed, while the freeways are the most heavily impacted. Despite the two scenarios having very similar daily VKT, the resulting network performance substantially varies.

Figure 1.5 shows the changes in average travel time during the peak period (average for AM and PM peaks) by origin TAZ to all the other TAZs for 75% MPR of AVs and 75% MPR of CAVs scenarios. For 75% MPR of AVs, the results indicate that most areas (other than Person and Chatham Counties and parts of Orange and Durham Counties) experience a minimum of 2% increase in travel time on average for originating trips. Trips originating from Wake County are impacted the most. Wake County has the largest share of VKT in the Triangle Region (55.6% of the total daily VKT) and a large portion of the freeway network. With reduced capacity and induced travel demand, this county is at the highest disadvantage in terms of transportation network performance. On the other hand, if the 75% MPR of CAV materialized by 2045, Wake County would see the greatest improvements in peak-period speed and travel time thanks to the changes in highway capacity. These findings suggest that counties with higher travel demand are more prone to disruptive technologies. This outcome should be considered by public agencies as they aim to plan for the future. Wake County has the highest population and is the fastest-growing county in the state, requiring a lot of attention from decision makers to ensure satisfactory network performance in the future.

Sensitivity Analysis of the Percieved Value of Time

The results presented in the previous section are based on an assumed 50% reduction in the IVTT coefficient, which reflects a significant decrease in the impact of in-vehicle travel time on an individual's utility. Although this assumption is in line with previous related research (Kim et al. 2015; Zhao and Kockelman 2018), some researchers have argued that smaller reductions in IVTT should be considered because the majority of the population is not willing or able to spend the time in the vehicle productively (Singleton 2019; Schoettle and Sivak 2014b). In this section, the sensitivity of the outcomes on the assumed IVTT coefficient reduction is tested. The six AV and CAV market penetration scenarios previously presented are evaluated for a 25%, 50%, and 75% reduction in the IVTT coefficient of traditional vehicle travel, resulting in 18 scenarios. Figure 1.6 presents the results for daily VKT, daily VHT, daily delay, and peak-period freeway speed in terms of percentage changes in comparison to the base scenario.

The results indicate that, for any given market penetration scenario, the daily VKT, VHT, and delay increase where there is a higher reduction in the IVTT coefficient. This relationship exists because a decrease in the IVTT coefficient increases the number of drive-alone trips and, in some cases, the trip length as well, resulting in increased VKT, VHT, and delays. However, the differences in the results caused by the change in the IVTT coefficient are relatively small and typically range between 0.5 and 1 percentage



(a) Percentage change in daily VKT and daily VHT compared to base scenario

(b) Percentage change in daily delay and peak-period freeway speed compared to base scenario

Fig. 1.6 Sensitivity analysis for reduced burden of travel by AV and CAV.

points. Nevertheless, changes in the IVTT coefficient could result in a substantial increase in VKT and VHT for metropolitan areas with well-developed transit systems serving a large proportion of the population. The Triangle Region has a bus network which is used by less than 1% of the population for commuting to work, and the vast majority of the trips happen by personal vehicle. Changes in the IVTT coefficient could lead to a notable increase in VKT and VHT for metropolitan areas with high transit ridership even if a small percentage of the population switches to personal-vehicle travel.

1.6 Conclusion

This study predicts the network-level effects of privately-owned AVs and CAVs in the Triangle Region, North Carolina, for the year 2045 by integrating a number of scenarios into the region's travel demand model. The chapter focuses on improving the understanding of researchers and practitioners regarding the implications of private AV adoption compared to private CAV adoption for the performance of transportation networks. Both a conservative and an optimistic market penetration scenario, with 30% and 75% MPR of AVs and CAVs, respectively, are envisioned for the year 2045. Sub-scenarios are generated to provide insights on the differential impacts of AV and CAV market penetration. Each scenario is associated with freeway and highway capacity changes which are based on microsimulation analysis of AVs and CAVs that accounts for interactions between AVs, CAVs, and traditional vehicles. A 30% increase in trips by individuals between 12 and 17 years old and 65 years old or older is assumed for relevant trip purposes. In addition, the impact of in-vehicle travel time on an individual's utility for a trip by personal vehicle is reduced to reflect the decreased burden of travel time when traveling by self-driving vehicles. The network-level impacts are reported in terms of daily vehicle-kilometers traveled (VKT), daily vehicle-hours traveled (VHT), daily hours of delay, and freeway peak-period speed. Figures are also used to demonstrate the changes in link flow and peak-period link speed for the Triangle Region's transportation network.

Overall, the results indicate that with induced travel demand, capacity adjustments, and reduced value of travel time, people will make more and longer trips by personal vehicles, resulting in up to a 3.6% increase in daily VKT in the Triangle Region. The findings significantly vary by the rates of AV and CAV adoption. Most importantly, the estimated impacts due to AV adoption are notably different from the impacts of CAV adoption. A 75% MPR of personal AVs is found to deteriorate the network's performance, resulting in a 5.4% increase in daily VHT, and a 17.2% increase in daily hours of delay. The opposite holds for CAV adoption, which is shown to lead to lower peak period link speed and less congestion. It becomes evident that the improvements in network performance largely depend on the effect that emerging vehicle technologies will have on capacity. The conservative driving behavior of AVs that only depend on sensors to navigate traffic has been found to reduce the network's capacity (Adebisi et al. 2020; Bierstedt et al. 2014; Samandar et al. 2020). Microsimulation findings suggest that significant gains in capacity can only be expected with a relatively large market penetration of CAVs (Samandar et al. 2020). Currently, the auto manufacturing industry and other supporting industries are focused on developing vehicle automation, while vehicle connectivity is a secondary interest at best. For example, Toyota recently abandoned their initial plan to install communication technologies in their vehicles, claiming several factors, including lack of

commitment from other automakers and limited governmental support (Shepardson 2019). In light of these uncertainties related to the availability of CAVs in the near future, it is important for state and regional agencies to understand that it may take several decades until transportation systems are positively impacted by emerging vehicle technologies, if privately- owned vehicles dominate the market. In addition, this study demonstrates that decision makers should expect that the network conditions may deteriorate during the period of transition from traditional vehicles to AVs and CAVs if the adoption of AVs is higher compared to CAVs. This study also finds that the negative as well as the positive impacts are higher in areas with initially higher travel demand, emphasizing the need for drawing adequate attention to those areas. Even though this study does not evaluate shared AV and CAV scenarios, it highlights the fact that private ownership will not lead to system-wide benefits unless there is a substantial CAV adoption rate, encouraging public agencies to consider policies and emerging mobility pilots that will lead to reduced vehicle ownership in the near future.

As for its methodological contribution, this chapter demonstrates how the results from microscopic simulation and macroscopic travel demand model can be integrated to simulate realistic future scenarios. Unlike most studies that focused on region-wide adoption of autonomous vehicle technologies, this chapter introduces capacity adjustments based on the outputs from a microscopic simulation tool that accounts for different car-following and lane changing behaviors of AVs and CAVs, and their interactions with human-driven vehicles. This microsimulation basis enabled investigation into the expected impacts where higher MPR of these technologies might lead to a decrease in overall capacity, which have been overlooked in most of the other studies. This study discusses the possible changes in travel behavior due to the advent of AVs and CAVs, and manifests how to incorporate those impacts within the bounds of the current regional travel demand model. The methods and findings of this chapter are of national as well as global importance as features of the travel demand model of the study area resembles most of the other travel demand models that are being used in other parts of the country and different regions of the world. Various statewide and regional planning organizations have already realized the needs for reshaping their models to incorporate AV and CAV-related changes (Cottam 2018). As billions of dollars are expected to be spent in the development of AV and CAV technologies, it is critical for transportation planners and government agencies to ensure that the benefits of these technologies can be harnessed while minimizing any potential negative impacts.

The limitations of this study are mainly related to restrictions imposed by the Triangle Regional Model and availability of relevant data. Specifically, this study is limited by the lack of mode choice models with personal AV or CAV options for the Triangle Region and the lack of necessary household survey data for developing such models. For this reason, the market penetration of AV and CAV is simulated assuming higher-income households as potential adopters. However, this limitation is not unique to this specific travel demand model or region, and this study demonstrates a potential approach that could be followed by other researchers or practitioners when facing similar restrictions. In addition, this paper does not analyze the network-level impacts of changes in individuals' parking behavior and leaves this important topic for future research. It is possible that AV and CAV owners would relocate their vehicles to avoid parking costs, therefore creating empty-vehicle trips leading to increased congestion and delays, especially in the case of high AV adoption (compared to CAV). It is critical to study different scenarios related to vehicle relocation for parking while considering important factors such as the origin and destination zones that are more likely to experience such trips, how this parking behavior may differ by trip purpose, the parking capacity of different zones, the number of individuals who are offered free parking by their employer and would not be interested in relocating their vehicles, and the potential policies that public agencies may implement to discourage such parking behavior.

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Chapter 2
Parking Policies for Private Connected and Autonomous Vehicles and their Effect on Transportation Network Performance

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2.1 Introduction

Autonomous vehicles (AVs) and connected-autonomous vehicles (CAVs) are likely to be introduced in American cities in the near future (Phillips, 2018). AVs and CAVs have the potential to bring long-term changes in the urban built environment. One of the major factors with significant implications in shaping and regulating the development patterns of urban areas is parking policies. In Central Business District (CBD) areas with high employment densities, carefully planned parking policies are imperative to control present traffic flows and to handle the future growth. At high levels of automation, AVs and CAVs can reshape the parking needs for dense urban areas because they remove the proximity constraints, i.e. parking options are no longer limited to the spaces close to the final destination (Millard-Ball, 2019). On the contrary, relocation of vehicles from urban cores could free up valuable spaces. Reduced parking demand might provide opportunities to introduce more productive land-use developments. Innovative policies like imposing taxes on empty vehicle trips, on-street pricing schemes for non-resident vehicles in residential areas, and subsidized

parking facilities outside CBD might control the relocation of empty AVs/CAVs and at the same time open up new revenue sources for the city authority.

The objective of this chapter is to analyze the impacts of potential parking relocation scenarios for autonomous and connected vehicles in the Triangle Region, North Carolina. This study uses the Triangle Regional Model (TRM), an aggregate trip-based travel demand forecasting tool to analyze different parking relocation scenarios for the year 2045. A number of different parking scenarios, each with different parking policy implications are analyzed for a fixed and significant market share of autonomous vehicle technology. Vehicle owners may be more likely to relocate their vehicles instead of parking inside CBD areas when they experience an overall improvement of traffic flow in the roadway network. Recent studies have suggested that CAVs are likely to improve freeway capacity while AVs are expected to maintain longer headways and be more conservative leading to capacity reductions (Samandar et al., 2020a; Hasnat et al., 2020). For this reason, this chapter primarily focuses on CAVs, and plans to consider AVs in the future. This study improves on previous related research (Kockelman et al., 2017; Vyas et al., 2019; Millard-Ball 2019; Zhang & Guhathakurta, 2017, 2018; Zhang & Wang, 2020) by simulating multiple parking scenarios into a full-scale regional travel demand model and analyzing a wide range of parking policies. The impacts of different parking policies related to personal CAVs on transportation system are reported in terms of network-level performance indicators, such as VMT, vehicle-hours traveled (VHT), delay, travel speed and travel times. Methods and findings of this study will help metropolitan planners, city officials, and departments of transportation (DOTs) to have a better perspective about the wide range of possible outcomes accompanied by mass adoption of personal CAVs. This will help in forming new and innovative parking policies to avert or alleviate any adverse situation in the future with high MPR of emerging vehicle technologies.

2.2 Literature Review

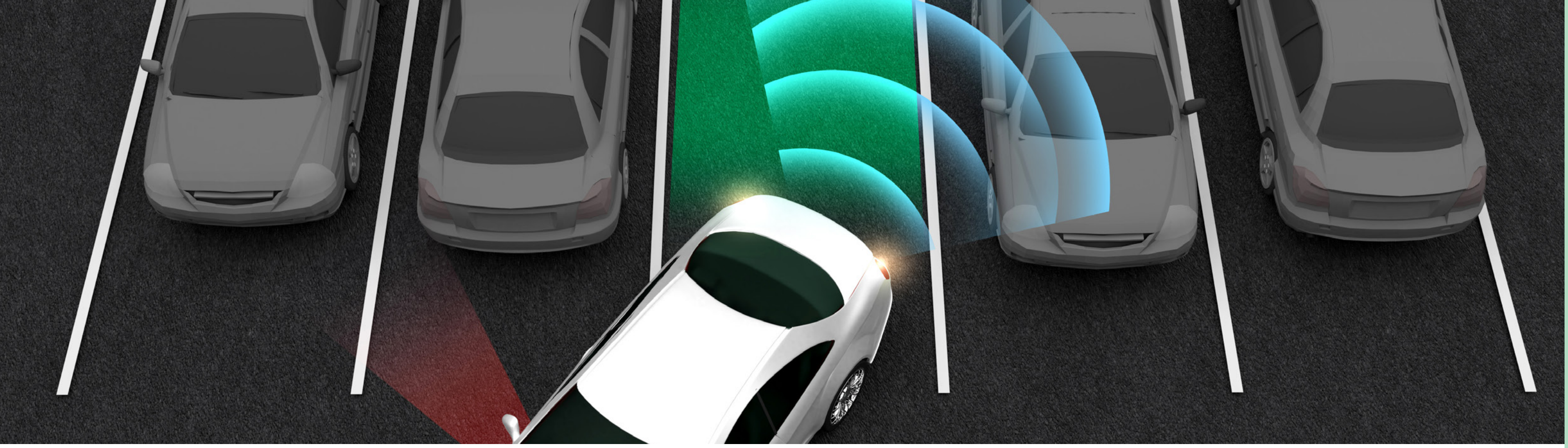
A number of studies have looked into the parking issues related to different emerging vehicle technologies for different regions of the country. Almost all of the studies have focused on high-density downtown areas. Millard-Ball (2019) analyzed the impact of parking relocation trips by personal AVs on downtown San Francisco area. Personal AVs coming to the downtown area were provided three options: parking in peripheral locations outside the CBD, going back home or cruising around the network to avoid paying parking fees. The study simulated these cruising vehicles in a microsimulation environment and reported that AVs could create near gridlock situation in the network as more of them decide to cruise around the network at lower speeds. Using 2015 parking inventory and parking cost data, the study suggested that the parking demand in downtown area could be reduced by 60%. A major portion of the trips (40%) destined to downtown area might choose to cruise around the network while about 20% trips might choose to relocate elsewhere.

Harper et al. (2018) used agent-based simulation to model the impact of AVs on parking revenues in the city of Seattle, Washington. The study allowed AVs to relocate from downtown parking lots to nearby unrestricted parking spots which provided lower cost options. The results indicated that in order to find the cheapest available parking option a single AV could travel as much as 4 miles/day and 8.4 miles/day at 25% and 100% MPR, respectively. The study analyzed the possible decline in revenue stream generated from parking related sources and pointed towards a future where it might be economically infeasible to operate large parking lots in downtown areas. Zhang & Guhathakurta (2017) and Zhang et al.

(2015) studied the parking demand for small MPR of shared AVs (SAVs). Zhang & Guhathakurta (2017) analyzed parking demand for Atlanta considering 5% MPR of SAVs where 5% of the residents are assumed to give up personal vehicles and use SAVs. As per 2013 travel data, this translated into 32,365 daily trips starting and ending within 208 TAZs of Atlanta. The study found that the introduction of a charge-based parking system compelled the SAVs to wander around rather than park. Hence, the policy resulted in lower parking demand, but generated greater VMT. A similar methodology was adopted by Zhang et al. (2015). The authors introduced 2% MPR of shared AVs into a 10 square-mile hypothetical grid city to serve the travel needs of 10,000 clients. The model introduced different threshold values on empty shared AV cruising time. Increasing this threshold reduced parking needs as SAVs would rather cruise than park, and distributed parking to lower cost areas within the city, instead of concentrating in the higher cost central areas.

In summary, previous studies either used agent-based models to simulate real world urban cities or introduced hypothetical small-scale city to rigorously examine the parking issues related to personal AVs and SAVs. Few other studies that included parking related assumptions in full-scale regional models, focused on incorporating different pricing or demand options (Kockelman et al.; Nair et al., 2018; Vyas et al., 2019). Some studies used the latest available parking inventories and analyzed different options with AVs and/or SAVs (Millard-Ball, 2019; Harper et al., 2018; Zhang & Guhathakurta, 2017), while some studies introduced parking strategies for future years (Zhang & Wang, 2020). Different policy implications analyzed in previous studies include hourly rates for on-street parking (Zhang & Guhathakurta, 2017; Zhang et al., 2015), entrance-based parking fees (Zhang & Guhathakurta, 2017), time-based empty vehicle fees (Zhang & Wang, 2020), and cruising in the network to avoid parking fees (Millard-Ball, 2019). Most of the previous literature reported their major findings in terms of the changes in parking demand (Zhang & Guhathakurta, 2017; Zhang et al., 2015), generation of extra VMTs (Zhang & Guhathakurta, 2017; Zhang et al., 2015), spatial distribution of parking relocation trips (Zhang & Wang, 2020), and economical impact from reduced revenue generation (Harper et al., 2018).

This study contributes to the existing literature by incorporating parking relocation scenarios related to emerging vehicle technologies into a full-scale regional travel demand model. A number of parking policies are implemented in the regional travel demand model. In addition, this study measures the impacts of different parking policies in terms of network-level performance indicators, such as travel time, travel speed, delays, and VMTs.

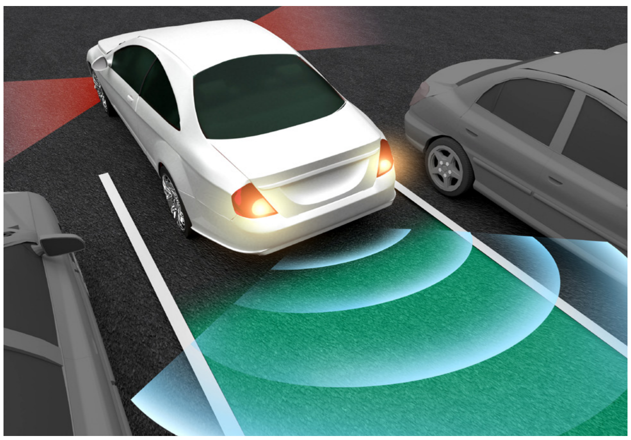


2.3 Parking Strategies

This study simulates CAV scenarios in the Triangle Regional Model which is the macroscopic travel demand model of the study region. Details of this model and the study region are described in Chapter 1 of this report volume. As described in the previous chapter, several sections of the TRM model have been modified to incorporate CAV related scenarios for the year 2045. For this study, we focus on the impact of parking relocation trips for a 75% market penetration rate of CAVs with 0% reduction in the in-vehicle travel time (IVTT) coefficient.

A number of parking relocation scenarios are analyzed in this study. Some of the key decision factors involved in building each of the scenario are: who would be willing to relocate their CAVs, what options will be available to them, what the probable costs will be, and what policies could reduce the negative impacts. In every scenario, the CAVs would drop the owner to his/her work location during the morning peak hour, relocate somewhere outside the CBD TAZs, and come back during the evening peak hour to pick up the owner. To avoid complication with chained trips, only the single-occupant vehicle (SOV) home-based trips to work (HBW) are considered in this study. From the base scenario run (with 75% MPR of CAV by 2045), it was found that during the peak hours, 84.4% of the HBW trips with SOV modes are generated from strata 4 and strata 5 households to the CBD TAZs. To be consistent with the TRM, MPR relocation options are introduced for this portion of the HBW trips.

The major motivation behind relocation is to find cheaper parking options than CBD areas. Currently, the maximum parking fee is $14/day in downtown Raleigh (Raleigh Transportation, 2019), $2/hour in downtown Durham (Nelson\Nygaard, 2018), and $1.5/hour in downtown Chapel Hill (Park on the Hill). Assuming an eight-hour workday, the maximum parking fees for Durham and Chapel Hill downtown are $16/day and $12/day, respectively. We assume that CAV owners will be willing to relocate their vehicles if they save at least 25% of their parking costs inside CBD areas. Hence, the maximum acceptable relocation costs are set equal to $12, $10.5 and $9 for HBW trips that end in Durham, Raleigh and Chapel Hill CBD areas, respectively.



The ubiquitous cost associated with relocating empty CAVs in every scenario is the CAV operating cost. AV operating costs assumed in previous literature varies from $0.21/mile to $0.5/mile (Millard-Ball, 2019; Zhang & Wang, 2020; KPMG, 2015). This study adopts a $0.21/mile operating cost for CAVs which includes $0.04/mile fuel cost and $0.17/mile non-fuel cost (Millard-Ball, 2019). The one-time purchase cost of electric CAVs is ignored here, considering the fact that CAV owners are more likely to perceive the marginal cost of CAV operation rather than the entire ownership and operating costs while deciding to relocate their vehicles.

The latest related parking study reported that 77.78% of employees in Durham and 50% employees in Raleigh either enjoy free or subsidized parking provided by their employers (UrbanTrans, 2007). From scenario 1 to scenario 5, it is assumed that this portion of the CAV owners will not be interested in giving up their low-cost parking options and adopt the idea of relocating their CAVs away from their working locations. Therefore, out of 84.4% of the total SOV HBW trips, 22.22%, 50% and 36.11% (average of Durham and Raleigh CBD) of the trips coming to Durham, Raleigh and Chapel Hill CBD areas, respectively, are considered as eligible to relocate their CAVs. In parking scenario 1, we assume that this eligible HBW trips will be sent back to home provided two-way travel costs between home and work TAZs are within the acceptable cost limit. In this scenario, it is assumed that long time parking for non-resident vehicles will not be allowed in non-CBD TAZ areas.

In scenario 2, CAVs are provided two parking options: go back to home or use on-street parking spaces available in different TAZs outside CBD areas. CAVs from each CBD TAZ are assumed to choose the least cost option. The on-street parking capacities are calculated as a percentage of the non-freeway roadway lengths provided in 2045 SE file of TRM. US lane mile statistics suggested that about 70% of the road lengths (excluding freeways and Interstates) are local roads (USDOT, 2017). 70% of the local roads are considered as residential roads in this study. Also, 30% of the residential roads are excluded to account for the driveways providing 70% of the residential road length to be available for on-street parking (Harper et al., 2018). Further, it is assumed that on a weekday, 50% of these parking spots are occupied by the resident vehicles (Harper et al., 2018). Therefore, in total, 35% of the residential roadway lengths are divided by 7 meters to have the on-street parking capacity of each non-

CBD TAZ. No fees are applied for on-street CAV parking in scenario 2.

Scenario 3 introduces parking restriction policies in the form of hourly parking fees for on-street parking, which could discourage parking on residential areas and minimize the impacts of empty CAV trips. All the assumptions of scenario 2 are maintained in scenario 3, except it includes hourly fees for on-street parking spots in non-CBD TAZs. Total parking cost for CAV relocation in scenario 3 includes the operating cost and the on-street parking fee. Parking fees for non-CBD TAZs are assigned as per the average land values. The highest rate of $2/hour is set for the TAZ with the highest average land value. For the rest of the TAZs, the parking fees are estimated to be inversely correlated to their average land value (Zhang & Wang, 2020).

Besides the hourly parking fees, scenario 4 and scenario 5 incorporate time-based and distance-based fees on empty CAV trips, respectively. Scenario 4 includes a fee of $0.1/minute and scenario 5 includes a fee of $0.1/mile for empty CAV trips. These costs are added to the operating costs and on-street parking fees to find the total cost of CAV relocation.

In scenario 6, it is assumed that none of the employers would provide free or subsidized parking facilities inside CBD areas for their employees. At higher MPR of CAVs, much of the trips destined for CBD areas might choose less costly parking options than paying higher parking fees inside CBD. This might lead to lower occupancy rates and thereby, lower revenues for downtown parking lots (Harper et al., 2018). Therefore, the overhead parking costs might be increased to cover the fixed costs of the parking facilities. This could motivate the employers to adopt parking cash-out programs for employees rather than paying higher parking prices. In such a scenario, all of the 84.4% SOV HBW trips generated from household strata 4 and 5 will try to find cheaper parking locations outside CBD. In scenario 6, it is assumed that all CAVs from these HBW trips will be sent back to their home TAZ, provided the two-way travel cost is lower than the parking cost in CBD areas.

Scenario 7 proposes a countermeasure to scenario 6 by installing parking facilities in the peripheral zones of the CBD areas that will accommodate the future parking needs at subsidized cost. A number of factors are considered to find out potential locations for future parking infrastructure, including average distance from the closest CBD area, total zonal area, population and employment densities, average household income, and available land for development. The urban TAZs located just outside the CBD areas attract much of the empty CAVs as they are closest to the CBD areas. However, compared to suburban and rural areas, urban TAZs have greater population and employment densities, higher land value, and more importantly, less space for future developments. On the contrary, building parking lots away from CBDs in suburban or rural areas would increase the average travel distance for CAVs to find cheaper parking options. This might increase the overall empty VMT and further deteriorate the network performance. Therefore, in this study, the peripheral parking facilities are incorporated in TAZs which are close enough to CBD areas so as to attract a greater number of CAV parking trips and already have large free parking lots, i.e. TAZs with large open areas next to stadiums and/or shopping malls.

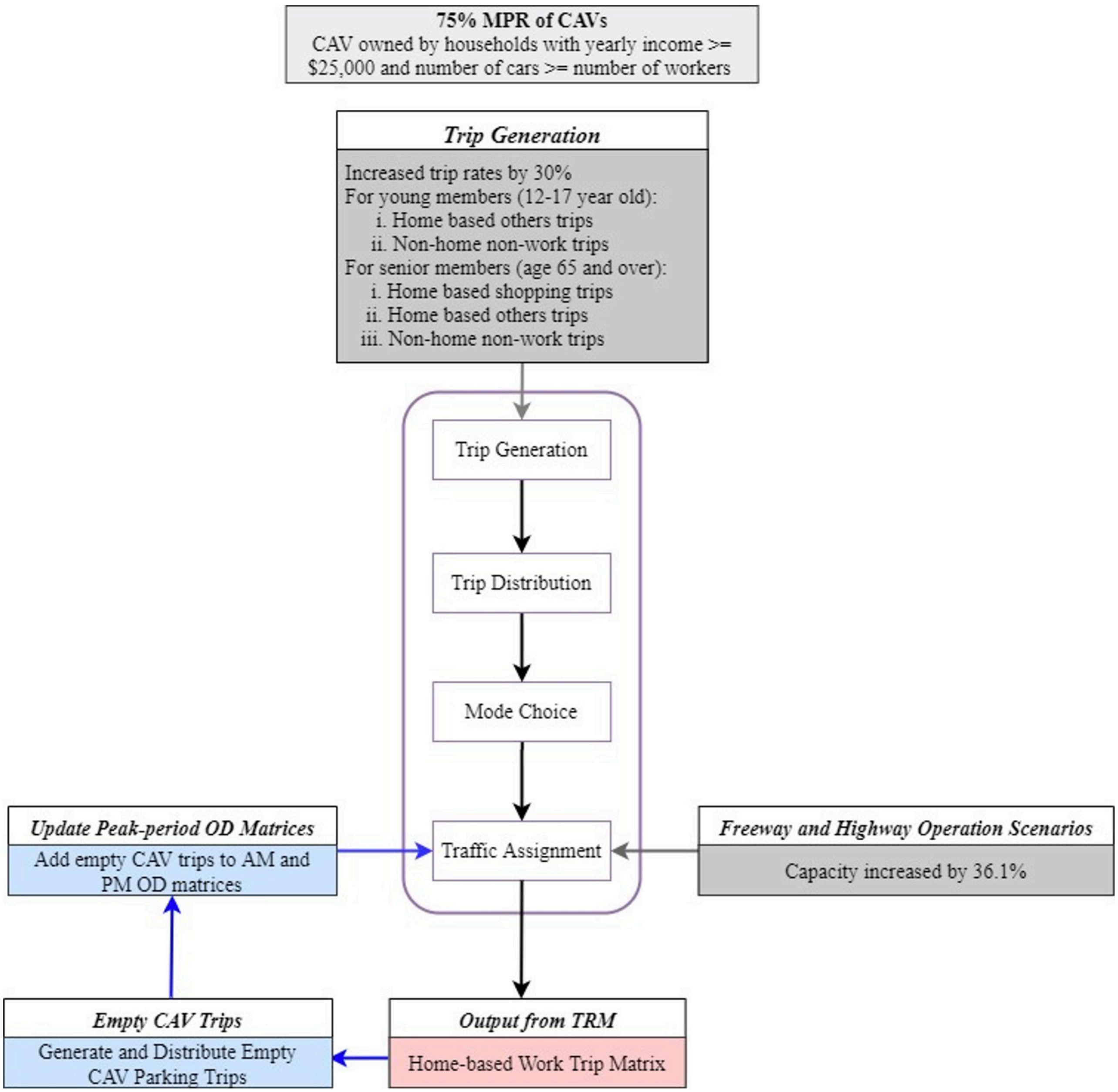


Fig. 2.1. Incorporating empty parking trips into Triangle Regional Model.

In summary the major parking policy implications of the scenarios:

- Scenario 1: On-street parking is not allowed at residential areas outside CBD TAZs
- Scenario 2: Free on-street parking is allowed at residential areas outside CBD TAZs
- Scenario 3: On-street parking is allowed for an hourly parking fee
- Scenario 4: Hourly parking fee for on-street parking and $0.1/minute empty ride fees
- Scenario 5: Hourly parking fee for on-street parking and $0.1/mile empty ride fees
- Scenario 6: Employer-provided free or subsidized parking are no longer available, on-street parking is not allowed at residential areas outside CBD
- Scenario 7: Subsidized parking facilities outside CBD TAZs

A python script is developed which works outside the TRM model to distribute the empty parking trips generated from HBW trips to different origin-destination (OD) pairs. For each CAV parking relocation, two extra trips are added: one in the shoulder-2 of AM peak hour (8:30-10:00 AM) assuming CAVs would start looking for parking options after dropping owners at work during the AM peak, and the other into the shoulder-1 of evening peak hour (3:30-5:00 PM) assuming CAVs will start early form parked locations to pick up owners after office hours. The TRM traffic assignment module is re-run using these modified OD matrices to find out the network-wide impacts. Figure 2.1 presents a flowchart that shows how the parking scenarios are simulated in the TRM.

Summary of Findings

- Parking relocation trips from empty CAVs could increase the daily delay by 44%.
- A single CAV could travel as much as 10.5 miles to find parking at reduced cost.
- Highest negative impacts will be experienced in and around the CBD areas.
- On-street parking fees coupled with time-based fees on empty CAV trips will provide better network performance than other parking policies.

2.4 Analysis and Results

Spatial Distribution of Empty CAV Trips

The spatial distribution of the empty CAV trips is presented in Table 2.1. In scenario 1 and scenario 6, the total number of HBW trips that try to relocate elsewhere are 57,000 and 148,912, respectively. CAVs travel back to home TAZ in scenario 1 and 6 as on-street parking by non-resident vehicles is not allowed at TAZs outside the CBD. The only cost considered by the owners in these two cases is the $0.21/mile CAV operating cost. 3,759 trips in scenario 1 (6.6% of 57,000) and 14,797 trips (9.9% of 148,912) in scenario 6 decide to park as before (inside the CBD) as the two-way travel cost is above the set cost limit. These two scenarios have higher one-way trip lengths as the empty home TAZs are distributed all around the TRM study area. Scenario 1 and scenario 6 have average one-way trip length of 9.92 miles and 10.49 miles, respectively.

On-street free parking at TAZs outside the CBD is allowed in scenarios 2 and 5. In these scenarios, CAVs seek to relocate to the closest non-CBD TAZ with parking capacity greater than 0. Once the on-street parking capacity is reached, CAVs seek to relocate to the next closest TAZ with parking capacity greater than 0. As shown in Figure 2.3, the empty CAV trips are more concentrated around the CBD areas in these scenarios. In scenario 2, all 57,000 trips are relocated to different TAZs other than the CBDs, and only 780 trips (1.4%) travel back to home TAZs. This scenario has the lowest one-way trip length of 1.87 miles. Hourly rates for on-street parking are applied in scenario 3 to scenario 5. In scenario 3, CAVs have to travel a little further away from the CBD compared to scenario 2 in order to find cheaper parking spots. The average one-way trip length in scenario 3 is 2.05 miles, which is 9.6% higher compared to scenario 2. Also, 6,400 trips travel back to home, which is 11.1% of the total relocating trips compared to 1.4% in scenario 1. In scenarios 4 and 5, empty trip fees are applied in the form of $0.1/minute and $0.1/mile rate, respectively. This reduces the number of empty CAV trips travelling back home and the one-way average trip length compared to scenario 3. The average on-street parking occupancy is above 90% for all the scenarios from 2 to 5. The spatial

	Parking scenario	1	2	3	4	5	6	7
Number of CAVs parked in a single TAZ/Facility	Maximum	392	480	573	480	480	983	4000
	Average	22	119	137	121	124	52	3632
Parking spread	Total TAZs	2425	485	420	479	467	2576	41
Empty CAV trips	Going back to home	53241	780	6400	627	716	133815	2985
	Parking on-street/ on peripheral facility	0	56920	51300	57073	56984	0	145927
	Total empty trips (both way)	106482	115400	115400	115400	115400	267630	297824
One-way trip length for empty CAVs	Average	9.92	1.87	2.05	1.95	1.99	10.49	2.86
	Maximum	28.56	9.9	5.36	5.04	5.09	28.56	14.25
	Minimum	0.04	0.16	0.18	0.15	0.18	0.04	0.2
Parking occupancy (% of capacity)	Average	_	95.70%	94.76%	93.91%	94.60%	_	90.80%
	Maximum	_	100%	100%	100%	100%	_	100%
	Minimum	_	3.20%	1.30%	0.50%	2.60%	_	5%

Table 2.1. Distribution of parking trips for empty CAVs.

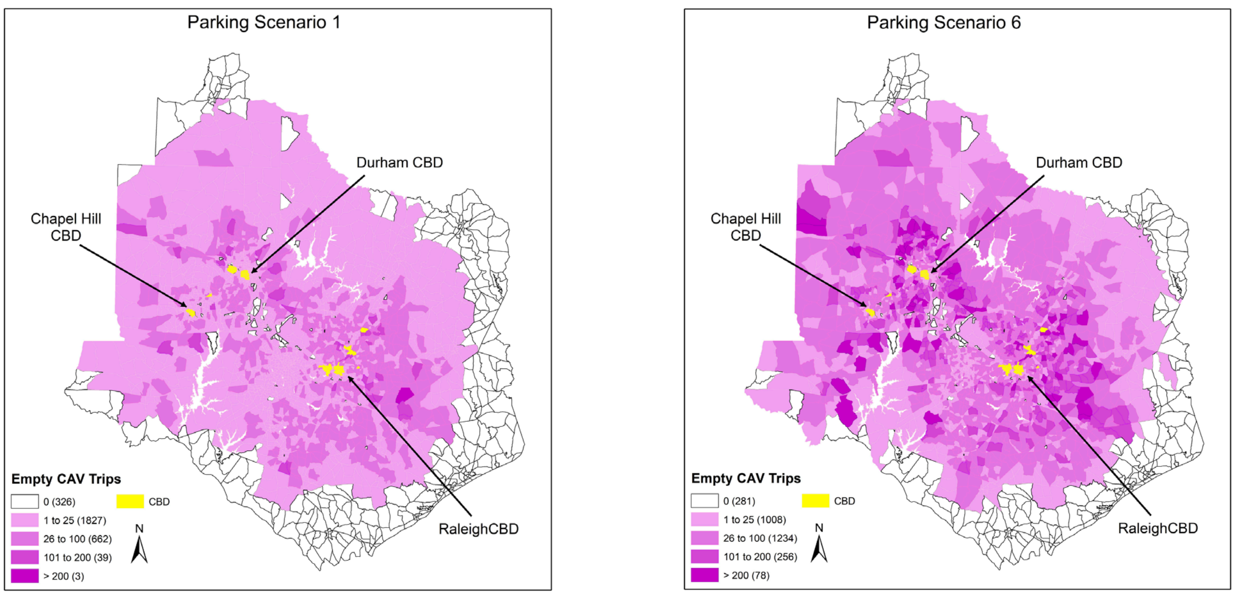


Figure 2.2. Spatial distribution of empty CAV trips (a) Parking scenario 1 and (b) Parking scenario 6.

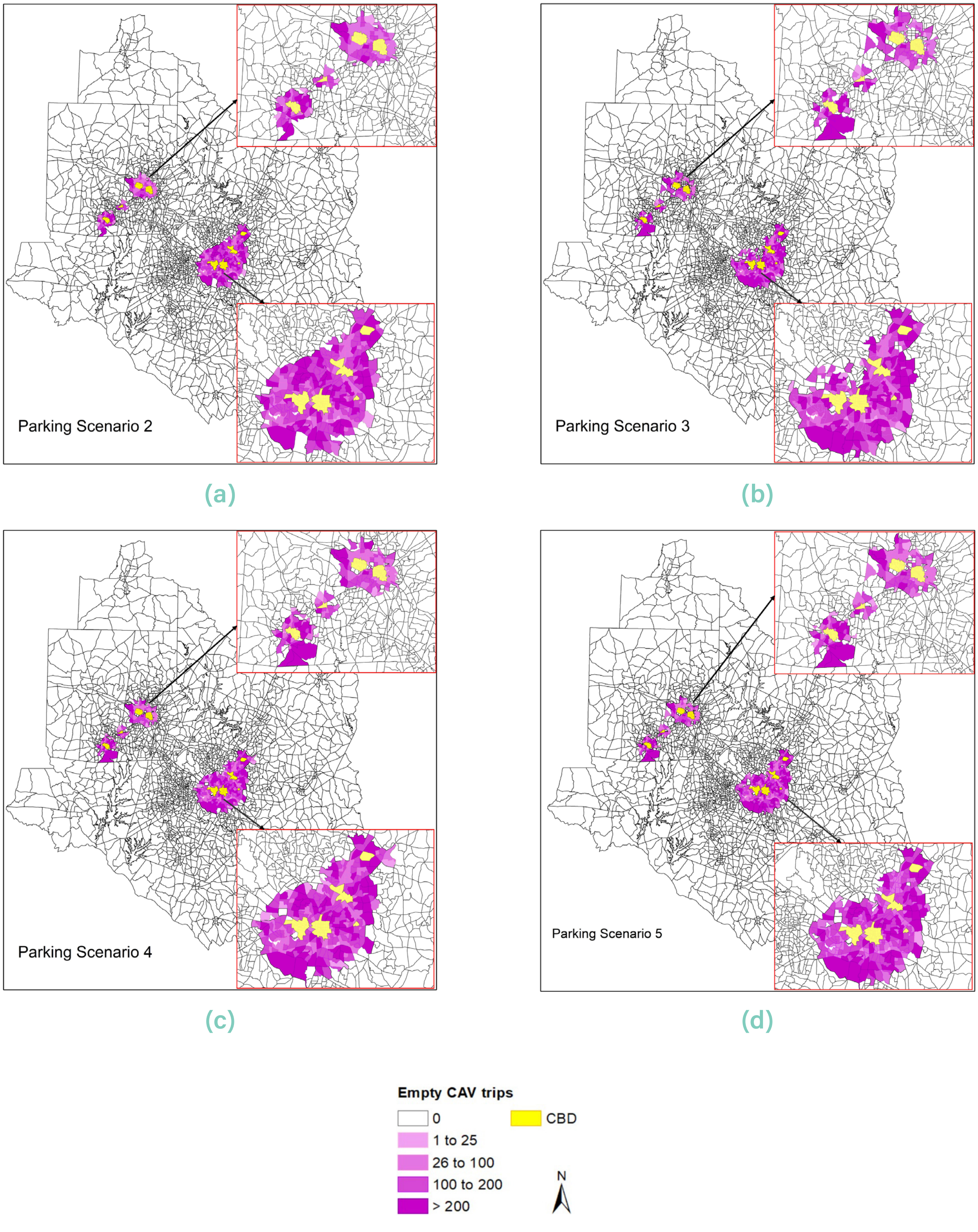


Figure 2.3. Spatial distribution of empty CAV trips (a) Parking scenario 2, (b) Parking scenario 3, (c) Parking scenario 4 and (d) Parking scenario 5.

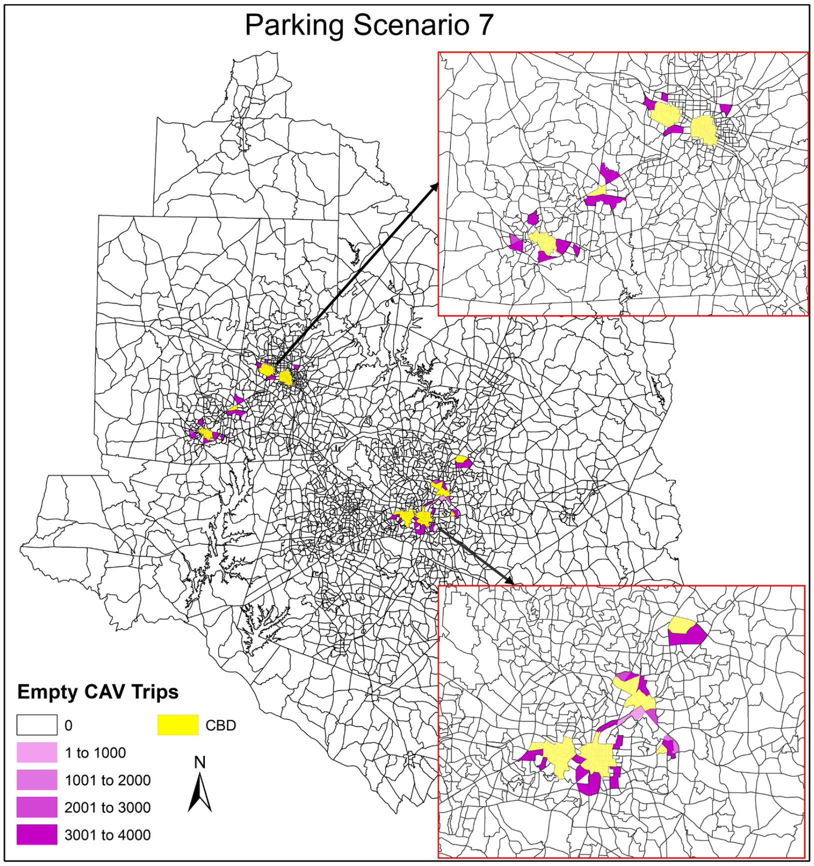


Figure 2.4. Spatial distribution of empty CAV trips (a) Parking scenario 1 and (b) Parking scenario 6.

distribution shows that the CAVs avoid some of the high-priced non-CBD TAZs surrounding the CBD areas in scenario 3. However, in scenarios 4 and 5, on-street parking reaches close to capacity as time-based and distance-based fees limit the trip duration and tip lengths of empty CAVs, respectively.

In scenario 7, 41 non-CBD TAZs are selected to house the empty CAVs from HBW trips into subsidized parking facilities. In this scenario, 2,985 out of 148,912 trips travel back to home TAZs to avoid paying the subsidized parking fees. This reduces the average one-way trip lengths of empty CAVs to 2.86 miles compared to 10.49 miles in scenario 6. On the other hand, it increases the density of empty CAV trips in the non-CBD TAZs surrounding the CBD areas (Figure 2.4).

Network-level Impacts

Outputs from the TRM traffic assignment module provide the network-level impacts of the simulated parking scenarios in terms of different performance measures. Table 2.2 summarizes the

Parking Scenario	Vehicle-miles traveled		Vehicle-hours traveled		Peak-period Freeway speed		Peak-period Arterial speed		Daily delay		Average travel	
	Value	% change	Value	% change	Value	% change	Value	% change	Value	% change	Value	% change
Base	93168269	_	2537489	_	57	_	37.2	_	403472	_	25.09	_
1	94315912	1.23%	2601391	2.52%	56.7	-0.53%	36.9	-0.81%	437538	8.44%	25.28	0.76%
2	93428390	0.28%	2566268	1.13%	56.9	-0.18%	37.1	-0.27%	422543	4.73%	25.2	0.44%
3	93438409	0.29%	2566060	1.13%	56.9	-0.18%	37.1	-0.27%	422025	4.60%	25.19	0.40%
4	93434510	0.29%	2565334	1.10%	56.9	-0.18%	37.1	-0.27%	421528	4.48%	25.19	0.40%
5	93444259	0.30%	2566833	1.16%	56.9	-0.18%	37.1	-0.27%	422650	4.75%	25.2	0.44%
6	96472695	3.55%	2796869	10.2%	55.7	-2.28%	36.1	-2.96%	579327	43.59%	25.91	3.27%
7	94614800	1.55%	2721295	7.24%	56.2	-1.40%	36.6	-1.61%	546066	35.34%	25.92	3.31%

Table 2.2. Network-level impacts of CAV parking trips.

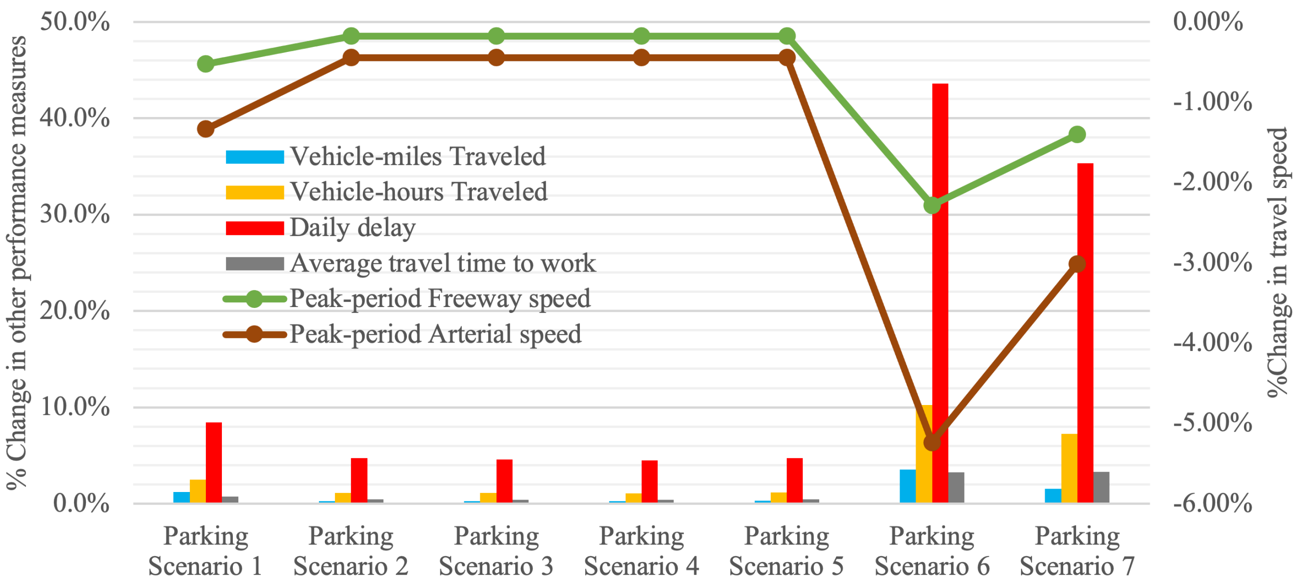
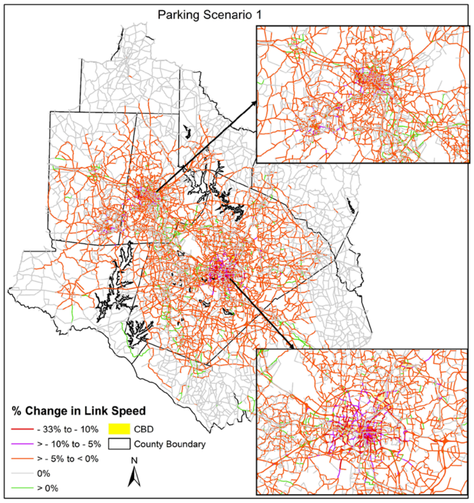
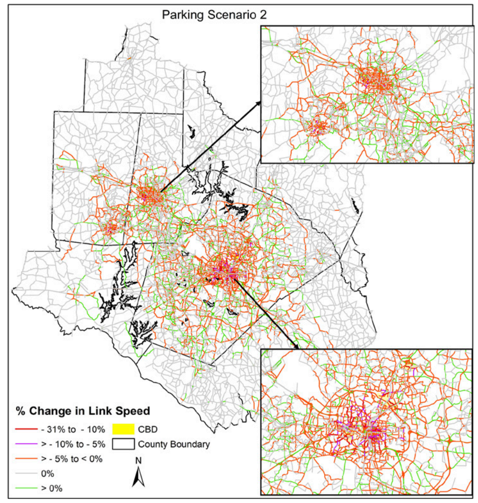


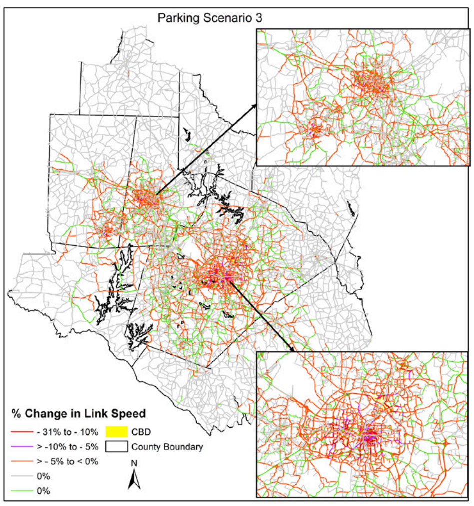
Fig. 2.5. Network-level impacts of empty parking trips.



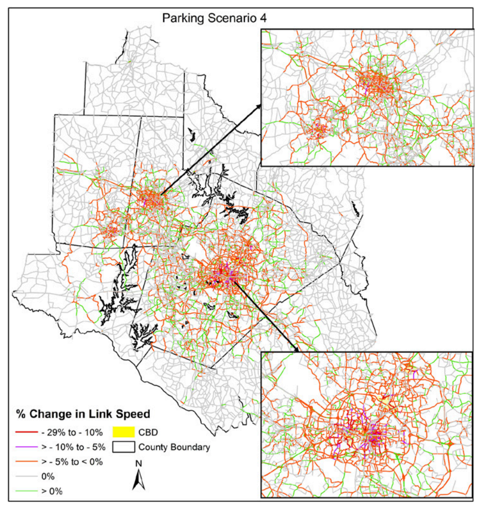
(1)



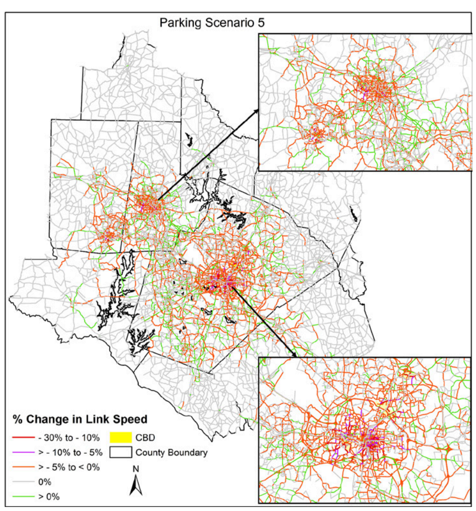
(2)



(3)



(4)



(5)

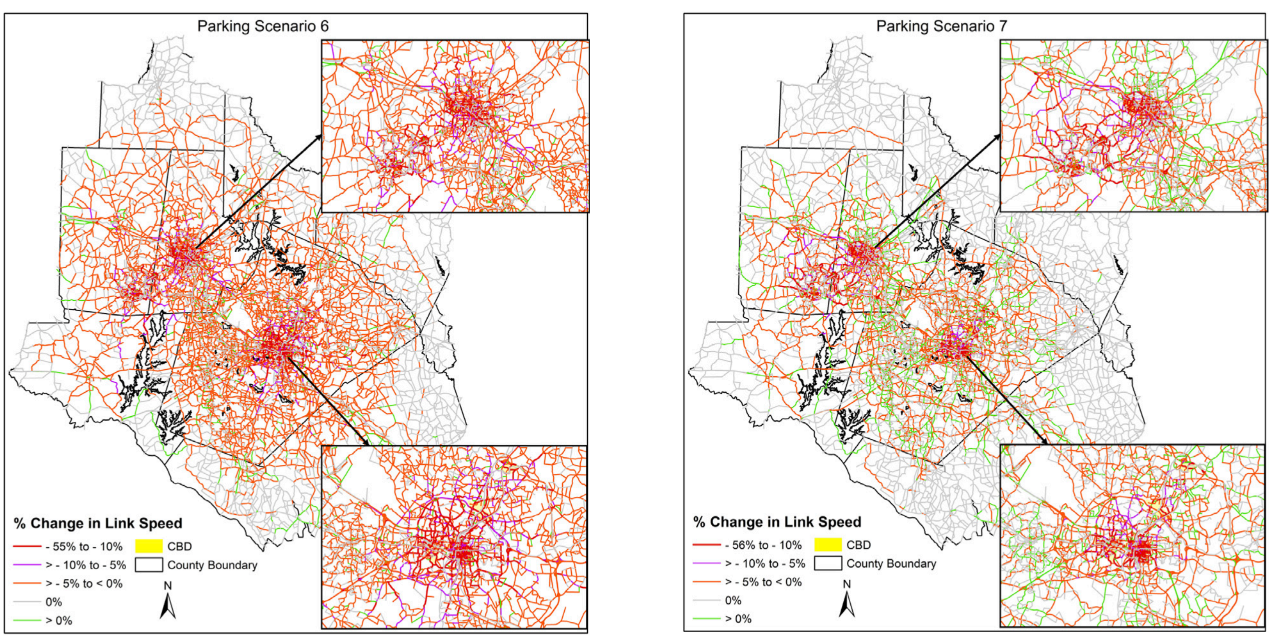
Fig. 2.6. Change in peak hour link speed during parking scenarios 1 to 5.

major performance indicators by parking scenario and the percentage changes compared to the base 2045 scenario.

In scenario 1 the daily VMT, VHT, delay, and travel time to work increases by 1.23%, 2.52%, 8.44% and 0.76%, respectively. On the other hand, average travel speed on freeway and arterial reduces by 0.53% and 0.81% respectively. Network performance improves in scenarios 2 - 5 where on-street parking is permitted. The lowest increase in daily hours of delay is found in scenario 4 where the CAVs have to pay on-street hourly parking fees and $0.1/minute empty ride fees. Scenario 6 and scenario 7 have the most adverse impact on the transportation network due to the higher number of HBW trips relocating to non-CBD TAZs compared to other scenarios. The daily VMT increases by 3.6% percent in scenario 6 and 1.6% percent in scenario 7. The daily hour of delay increases by 43.59% and 35.34% in scenario 6 and 7, respectively. Table 2.2 suggests that the parking scenarios have higher impacts on peak-period travel speed on the arterial roads compared to the freeways.

Taking a closer look into the link-level peak-hour traffic assignment outputs revealed significant impacts in some regions of the study area. Figure 2.6 and Figure 2.7 show the percentage changes in peak-period link speeds by parking scenario compared to the base 2045 scenario.

As seen in Figure 2.6 (a), in scenario 1, empty CAV trips negatively affect the link travel time in most parts of the study area. From scenario 2 to scenario 5, the adverse impact is mostly concentrated around the three CBD regions of the study area. The Raleigh downtown experiences the most adverse impact in all scenarios because more than half of the total HBW trips ends in this area. Scenario 6 has the highest negative impact on peak-period travel speed (Figure 2.7 (a)) because of the highest



(a) (b)

Fig. 2.7. Change in peak hour link Speed during (a) parking scenario 6 and (b) Parking scenario 7.

number of CAVs sent back to home compared to any other scenario. Peripheral parking facilities in scenario 7 help to reduce the impact from scenario 6. This, however, puts more adverse effects on the link travel speed for the non-CBD TAZs surrounding the CBD areas. Providing peripheral parking facilities ensures available parking space for all the CAVs looking to relocate outside CBD areas. This also ensures that the on-street parking spaces of non-residential TAZs will not be overrun by empty CAVs from nearby CBD areas. Fees collected from these subsidized parking facilities can work as a significant source of revenue for the local transportation authority. Some of the designated parking facilities might see occupancy rates as low as 5% (Table 2.1). Optimum locations should be selected for these parking facilities to have higher occupancy and ensure steady flow of revenues.

2.5 Conclusion

In this chapter, the implications of several parking policies including free and hourly on-street parking rates at non-CDB areas, and distanced-based and time-based tax on empty CAV trips are analyzed while distributing the empty CAV trips to non-CBD TAZs. The results show that on-street parking fees coupled with time-based fees on empty CAV trips lead to better network performance than other parking policies. This study also analyzes scenarios where employer provided free or subsidized parking facilities might not be available inside CBD areas. Sending all these additional trips to home results in 3.6%, 10.2%, 43.6% and 3.2% increase in daily VMT, VHT, delay, and average travel time to work, respectively. This also reduces the average peak-period travel speed on the arterials and freeways by 3% and 2.3%, respectively. Installing peripheral parking facilities at subsidized parking rates improves the network performance but results in much denser distribution of empty parking trips. It is found that, about 41 peripheral parking facilities, each with parking capacity for 4000 CAVs would be able to house all the peak-period parking demands from HBW trips. In all the scenarios, roadway networks inside and surrounding the CBD areas experience higher travel speeds. Among the three downtown areas, Raleigh downtown experiences the greatest reduction in peak-period travel speed compared to no-parking scenarios. This is due to the fact that, more than half of the region's employment is concentrated in this CBD areas.

Outputs of this study provide useful insights for future downtown parking and land-use policies. This study is limited to home-based work trips while other trip purposes (shopping and other trips) will be considered in future research. Single pricing scenarios are analyzed for on-street parking fees, and for time-based and distance-based empty CAV fees. Future studies should also look into the social impact of empty parking trips which can be revealed by analyzing the distribution of the parking trips into different neighborhoods.

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Chapter 3
Impacts of Autonomous and Connected-Autonomous Vehicles on Household Residential Location

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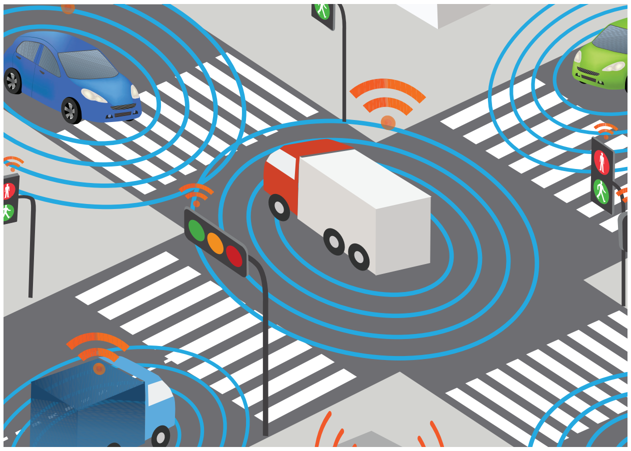
3.1 Introduction

The adoption of autonomous vehicle (AV) and connected-autonomous vehicle (CAV) technologies in the transportation sector will substantially impact the ways people and goods are transferred from one place to another. Although transportation stakeholders are eagerly waiting to harness the benefits of these technologies, they are also concerned about potential unforeseen consequences that might arise. Numerous studies have reported expected impacts on travel demand (Truong et al., 2017; Wadud et al., 2016; Sivak & Schoettle, 2015; Harper et al., 2016; Scribner, 2018), highway capacity (Markus Maurer, 2016; Le Vine et al., 2017), and safety (Koopman & Wagner, 2017; Anderson et al., 2014; Gruel & Stanford, 2016) due to a significant market penetration of AVs or CAVs. In addition to these direct impacts, long-term indirect changes in land use and metropolitan area development are likely to follow.

Widespread AV and CAV adoption is expected to change transportation network performance, which has been shown to significantly affect households' residential location decisions (Guo & Peeta, 2020; Bruns & Matthes, 2019; Bhat & Guo, 2004). CAVs are anticipated to substantially improve freeway capacity because of their ability to communicate with other CAVs and the infrastructure and operate safely with smaller headways compared to human driven vehicles (Shladover et al., 2012; Tientrakool et al., 2011). On the other hand, AV deployments are more likely to focus on traffic safety and incorporate decision algorithms that are more conservative compared to human driving, leading to capacity reductions and degraded network performance (Hasnat et al., 2021; Adebisi et al., 2020; Bierstedt et al., 2014). If the direct impacts of widespread adoption of AVs and CAVs on capacity and overall transportation



network performance are heterogeneous, then their long-term effects on metropolitan areas may also be different.

In this chapter, we simulate the changes in network demand due to privately owned AVs and CAVs in a US metropolitan area and predict households' location decisions to better understand the differential impacts of AV and CAV adoption on the urban form. Although it is uncertain whether AVs and CAVs in the US will be primarily privately owned (Zhang et al., 2018; Bansal et al., 2016) or operate as part of shared fleets (Krueger et al., 2016; Shen et al., 2017), this research concentrates on a potential future where private vehicles dominate the market of AVs and CAVs. We also explore whether the adoption of electric AVs and CAVs will result in substantially different outcomes compared to conventional-fuel AVs and CAVs. The study focuses on the Raleigh-Durham-Chapel Hill combined metropolitan statistical (CSA) area, also known as the Triangle Region, in North Carolina. AV and CAV scenarios for the year 2045 are modeled using the regional macroscopic travel demand model for the Triangle Region. Cluster analysis is also used to provide insights on the spatial distribution of the changes in network performance across the region. Household residential location in 2045 is predicted and analyzed using data from the Triangle household survey and the travel demand model simulation results.

Researchers have envisioned personal self-driving vehicles inducing suburbanization and dispersed land development (Litman, 2018; Meyer et al., 2017; Bansal et al., 2016; Zakharenko, 2016; Anderson et al., 2014), while shared self-driving vehicles offering fast and inexpensive service and attracting more people to live in high-density areas (Durand et al., 2018; Yap et al., 2016; Chen & Kockelman, 2016). However, quantitative research in this subject has been rather limited (Bansal & Kockelman, 2018; Carrese et al., 2019; Gelauff et al., 2019; Kim et al., 2020; Krueger et al., 2019; Moore et al., 2020; Zhang & Guhathakurta, 2018). Our study contributes to this limited literature and advances the understanding of the varying effects of AVs and CAVs, a topic that previous research has not addressed. In addition, we deviate from studies that have assumed excessive changes in travel behavior and roadway capacity because such changes are not supported by the latest related research (Singleton, 2019; Krueger et al., 2019; Adebisi et al., 2020). Our study introduces capacity adjustments based on microscopic simulation analysis that accounts for the interactions of AVs and CAVs with human driven vehicles. Furthermore, we do not assume a decrease in the value of travel time for AV and CAV commute trips. Value of travel time reductions have been based on the hypothesis that passengers of self-driving vehicles will be able to undertake productive activities while driving, such as working, reading, or sleeping (Singleton, 2019; Shaw et al., 2019). Research has shown that such productivity gains, which can be currently realized during travel on airplanes or fixed guideway transit systems, are possible for long-distance AV and CAV trips on limited-access facilities but may not be relevant for commute trips to work, which are typically shorter and include regular speed and direction changes (Singleton, 2019). Recently, Krueger et al. (2019) found no differences in the value of travel time between traditional and self-driving vehicles based on a stated choice experiment of commuters in Sydney, Australia.

This research can assist transportation agencies and metropolitan area planning organizations to gain a better understanding of the effects of AVs and CAVs on transportation system performance and distribution of households within a metropolitan area in the future. Although the direction of the changes may be already understood or anticipated, reliable predictions on their magnitude remain scarce. Furthermore, transportation engineers and urban planners can use the outcomes of this study to inform decisions and plans related to future land development and infrastructure investments.

The chapter is organized into eight sections. Section 3.2 discusses the literature on residential location choice as well as previous research on the impact of AVs/CAVs on residential location decisions. In Section 3.3, we describe the study region. The fourth section includes the study methodology and discusses how we estimate and predict residential location choice under a number of AV and CAV scenarios. Section 3.5 focuses on the analysis of household residential location preferences for our study region, and Section 6 discusses the network-level impacts of AV and CAV adoption. The predicted changes in household residential location for 2045 are presented in Section 3.7. The final section concludes the study.

3.2 Literature Review

Modeling Residential Location Choice

The determinants of households' choice of residential location have been studied extensively (de Palma et al., 2007; Lee et al., 2010b; Eliasson, 2010; Gehrke et al., 2019; Kroesen, 2019). The majority of past studies have used household survey data to develop discrete choice models where an individual or a household seeks to maximize their utility with respect to residential location (Akbari et al., 2020; Zolfaghari et al., 2012; Pinjari et al., 2011). The granularity of the unit of analysis, such as dwelling unit, traffic analysis zone (TAZ), and census geography, largely depends on the research question and the available dataset. Explanatory variables previously used in residential location choice models include built environment characteristics of home and work locations (walkability, street density, access to different destinations), residential unit features (size, number of bedrooms, price), household characteristics (owner or renter, size, age of the members, income, number of workers, number of children, vehicle ownership), individual-level information (age, education, income, commute time, commute cost), and neighborhood attributes (median household income, racial composition, proximity to downtown, parks, and schools) (Akbari et al., 2020; Zolfaghari et al., 2012; Pinjari et al., 2011, 2009).

Results from previous research suggest that commute time has an important but heterogeneous effect on households' residential location decision (Guo & Bhat, 2007; Zhou & Kockelman, 2009; Lee et al., 2010a; Zolfaghari et al., 2012; Zondag & Pieters, 2005). For example, Guo & Bhat (2007) found that single-person households and households with female workers have a stronger preference to reside closer to their

workplaces. Studies have also reported that young and single-person households prefer central, high-density areas, whereas families with children and high-income households are drawn towards low-density suburban areas (Pinjari et al., 2011, 2009). After reviewing a number of studies, Schirmer et al. (2014) concluded that the probability of relocating closer to urban city centers or moving to suburban areas changes over the households' life span and is influenced by different events like marriage, children, or job status. In this study, we develop a Mixed multinomial logit (MNL) model to explain and predict residential location choice for households in the Triangle Region. We follow the directions of previous research to select explanatory variables for our analysis. The methodological approach is presented in Section 3.4, and the data description and analysis are discussed in Section 3.5.

Impacts of Emerging Vehicle Technologies on Residential Location Choice

A few studies have simulated the changes in travel time and accessibility under private and shared AV scenarios and have used the results to predict the impacts on households' residential location choices (Zhang & Guhathakurta, 2018; Gelauff et al., 2019). Focusing on shared AVs, Zhang & Guhathakurta (2018) integrated a residential location choice model with an agent-based simulation model to identify household location changes for the Atlanta metropolitan area. A Mixed MNL residential location choice model was first developed to capture the current location choice behavior of households in Atlanta using data from a regional travel survey. The agent-based simulation assumed that all travel demand would be served by shared AVs that could only carry a single person at a time. Other assumptions included a decrease in parking spaces needed, lower cost of travel compared to traditional vehicles, and multitasking opportunities during travel which were reflected by a 25% to 100% reduction in the perceived cost of in-vehicle travel time. Based on these assumptions, a 48.4% to 72.4% decrease in commuting travel cost was estimated, which led to most households choosing to reside further away from their workplace and the central business district (CBD) (Zhang & Guhathakurta, 2018). Gelauff et al. (2019) used a spatial general equilibrium model to simulate potential population migration between city and rural areas in the Netherlands under privately owned and shared AV scenarios for the year 2050. The study assumed that private, fully autonomous vehicles would provide more productive use of in-vehicle travel time compared to traditional vehicles and therefore, reduced the perceived in-vehicle travel time cost by 20%. Shared AVs were assumed to provide demand response ridesharing, be more efficient than traditional public transport, but not as efficient as personal vehicles due to detouring for other passengers; these assumptions were reflected in a 20% increase in the perceived cost of in-vehicle travel time compared to traditional vehicles. In addition, Gelauff et al. (2019) assumed zero changes in transportation network performance due to automation, expecting that improvements in capacity would be counterbalanced by higher travel demand, leaving travel time unchanged. The results suggested that adoption of fully autonomous private AVs would increase population density in non-urban areas by up to 1%, whereas adoption of fully autonomous shared AVs would increase population density in urban areas by up to 3%.

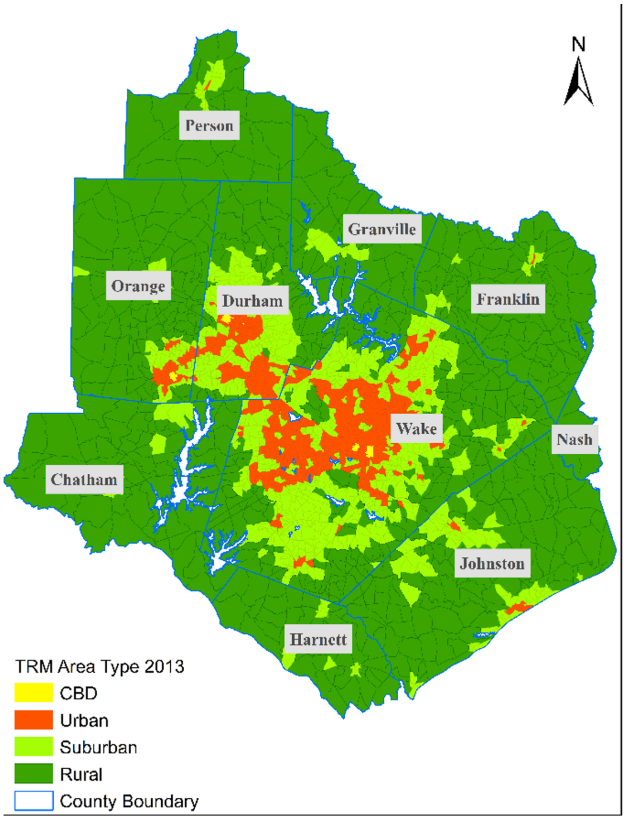
Researchers have recently conducted stated preference surveys related to residential location decisions and self-driving vehicle scenarios to better understand whether behavioral changes should be expected in the future (Bansal & Kockelman, 2018; Carrese et al., 2019; Kim et al., 2020; Krueger et al., 2019; Moore et al., 2020). Among other hypotheses, these studies examined whether individuals would consider moving their residence to a location that would require a longer commute if they had access to a personal vehicle with full self-driving capabilities, all else constant. It was hypothesized that people would be willing to commute longer if they felt that they could spend their commute time more productively; in that case, their perceived cost of in-vehicle travel time would be lower than that of traditional vehicles. Kim et al. (2020) found that only 11.0% of Atlanta residents would consider moving farther from work if they owned fully autonomous vehicles. Similarly, Bansal & Kockelman (2018), who conducted a survey in Austin, Texas, documented that 11.1% of the survey respondents would consider moving farther from the city center if they had access to personal fully autonomous vehicles. Moore et al. (2020) found that a larger percentage of respondents (25.8%) would be willing to move and increase their commute time by more than 10 minutes if they owned self-driving vehicles. The sample of that study was, however, skewed towards educated, full-time employed, non-Hispanic White individuals. Following a different approach, Krueger et al. (2019) asked survey respondents to choose between combinations of residential locations and commute mode options, and estimated the value of time for traditional and fully autonomous vehicles. Their results suggest no statistically significant differences between the value of travel time for fully autonomous and traditional vehicles.

Overall, stated preference surveys have not provided strong evidence of behavioral changes in residential location choice due to self-driving vehicle adoption for the majority of the population. Based upon these recent results as well as the analysis conducted by Singleton (2019), no changes are considered in the value of travel time in the AV and CAV scenarios for this study. Specifically, we assume that future changes in households' residential location are mainly an outcome of changes in commute travel time and accessibility due to widespread AV and CAV adoption, and not an outcome of more productive use of the time spent in a personal AV or CAV.

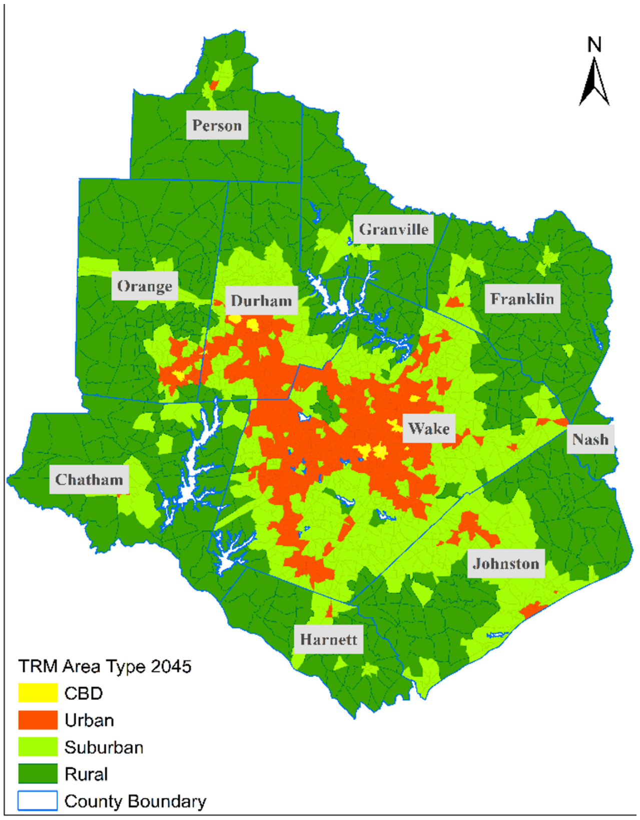
3.3 Study Setting

The Raleigh-Durham-Chapel Hill CSA, also known as the Triangle Region, is the second largest CSA in North Carolina. It covers 11 counties with a total area of 5510 square miles and a total population of 2,238,315. The three main population centers are the cities of Raleigh, Durham, and Chapel Hill, which are approximately a 20 to 30-minute drive apart. Growing numbers of high-skill job opportunities and multiple educational institutions have contributed to the region's high population growth. Currently, the median household income of the Triangle Region is 25% higher than the NC median household income and 10% higher than the US median household income (U.S. Census Bureau, 2019).

The Triangle Regional Model (TRM) is the Triangle Region's travel demand model. The TRM covers an area of 3380 square miles, that includes Wake, Durham, and Orange Counties, and parts of Chatham, Franklin, Granville, Harnett, Johnston, Lee, and Person Counties of the Raleigh-Durham-Chapel Hill CSA. The TRM region constitutes the study area for this research and is composed of 2857 traffic analysis zones (TAZs) (Figure 3.1). TRM scenarios representing present conditions are based on 2013 socioeconomic data for the region, while future conditions (up to year 2045) are modeled using socioeconomic predictions from the Triangle CommunityViz 2.0. The Triangle CommunityViz 2.0 is a tool that combines statistical and spatial analysis with inputs from stakeholders to predict the magnitude and location of future developments in the Triangle Region (Stantec, 2015; CommunityViz, 2018). It is estimated that between 2013 and 2045, the Triangle Region will experience a 76% increase in population and a 60.4% increase in employment (CommunityViz, 2018). The region is classified into four area types (CBD, urban, suburban, rural) based on employment and land-use density. Substantial growth is anticipated for the CBD, urban, and suburban areas in the next decades. Specifically, between 2013 and 2045, the CBD, urban, and suburban land areas are expected to increase by 226%, 65%, and 55%, respectively (Figure 3.1). Additional information on the region's socioeconomic characteristics is provided in Section 3.5.



(a) 2013



(b) 2045

Figure 3.1: Triangle Regional Model region in 2013 and 2045.

3.4 Methodology

Modeling Households' Residential Location Choice Behavior

Household preferences are modeled on the basis of random utility theory (McFadden, 1978). A location (in our case, a TAZ) is chosen by a household from a set of mutually exclusive alternatives if it provides the highest utility compared to all other alternatives. We use a Mixed MNL model that can account for correlation across alternatives and unobserved heterogeneity by allowing coefficients to vary across individuals (McFadden & Train, 2000). Several past studies on residential location choice have applied the Mixed MNL model to capture household or individual preferences (Pinjari et al., 2009; Habib & Miller, 2009; Zhang & Guhathakurta, 2018; Krueger et al., 2019).

We analyze data from 2356 households in the Triangle Region who participated in a household survey in 2016, assuming that each household can choose to reside in one of the TAZs in our study area. The utility that a household h ∈ (1, 2, . . . , H) derives from an alternative TAZ j ∈ (1, 2, . . . , J) is given by (Train, 2009):

$$U_{hj} = \beta' x_{hj} + \varepsilon_{hj} \quad \text{Equation 3.1}$$

where x_{hj} is a vector of explanatory variables of household characteristics and TAZ attributes, β is a vector of coefficients for household h, and ε_{hj} is an independently and identically distributed random error term that follows an extreme value distribution. The coefficients β are assumed to vary across households (due to variation of preferences) with density function $f(\beta|\varphi)$, where parameters φ represent the density function's attributes (for example, mean and standard deviation of the β). Under these assumptions, the probability of household h choosing TAZ i is given

$$P_{hi} = \int L_{hi}(\beta) f(\beta|\varphi)\, d\beta = \int \frac{e^{\beta' x_{hi}}}{\sum_j e^{\beta' x_{hj}}} f(\beta|\varphi)\, d\beta$$

Equation 3.2

A weighted average of the conditional logit probability $L_{hi}(\beta)$ for different values of β and weights provided by the density function $f(\beta|\varphi)$ (Train, 2009). This study uses a continuous form of the density function. For the model estimation, we specifically assume that coefficients follow a normal distribution, $\beta \sim N(b, W)$, with parameters b and W to be estimated. The Mixed MNL is estimated using simulated log likelihood. Exact maximum likelihood estimation is not feasible because Eq. 3.2 cannot be evaluated analytically (Train, 2009).

In addition, assessing the full set of alternative choices for each household in model estimation is not attainable, especially for large study areas with thousands of alternatives. Typically, a sub-sample of the universal choice set is randomly selected to serve as the choice set for an individual household (Guo & Bhat, 2007; Lee et al., 2010a; Zhou & Kockelman, 2009). Based on this method, n alternatives are selected at random from the available J alternatives, resulting in a choice set with n + 1 alternatives (including the 200 observed choice). Random selection of alternatives has been shown to yield consistent parameter estimation (McFadden, 1978). The value of n chosen by previous studies varies by unit of analysis, total number of alternatives in the universal choice set, household sample size, and modeling approach (Zhang & Guhathakurta, 2018; Zolfaghari et al., 2012; Yan, 2020). Following the direction of previous research, we randomly select n = 59 alternatives for each household from a universal choice set of J = 2819 TAZ alternatives.

Simulating Private AV and CAV adoption in the Triangle Region

Scenarios of adoption of privately owned AVs and CAVs are simulated in the Triangle Regional Model (TRM) for the year 2045. The TRM is an aggregated trip-based model for the Triangle Region with four major steps: trip generation, trip distribution, mode choice, and trip assignment. Increased trip rates for some AV or CAV user groups and capacity changes on certain highway segments are implemented to TRM v6 to simulate AV and CAV scenarios. Assumptions and analysis related to vehicle automation and connectivity, market penetration rate, induced demand, and changes in highway capacity are discussed in the following sections.

Market Penetration of Private AVs and CAVs

With respect to automation, this study focuses on self-driving vehicles (SAE Levels 4 and 5) (SAE International, 2018). In addition to self-driving capabilities, CAVs are assumed to have the ability to communicate with other CAVs and the infrastructure to collect traffic and other network information and to form platoons. This communication enables CAVs to operate more safely and efficiently compared to AVs. The market share of self-driving vehicles is predicted to reach its saturation point by 2060 (Lavasani et al., 2016) to 2070 (Litman, 2020). By 2045, up to 50% of the new vehicle sales and 40% of the total VMT could be generated by autonomous vehicles (Litman, 2020). In addition, studies have shown that early adopters are expected to be households with high income and multiple vehicles (Hjorthol, 2013; Petersen et al., 2006). Based on these findings from the literature, we consider two main market penetration scenarios: (i) a conservative scenario

(Scenario A), where high-income households with personal vehicles in the Triangle Region are assumed to own personal AVs or CAVs, and (ii) an optimistic scenario (Scenario B), where high income households with personal vehicles and medium-income households with as many or more vehicles than employed members own personal AVs or CAVs. Based on the Triangle Region household socioeconomic characteristics predicted for 2045, Scenario A translates into a 30% market penetration rate (MPR) of AVs or CAVs, while Scenario B translates into a 75% MPR of AVs or CAVs. To differentiate between the impacts of AVs and CAVs, additional sub-scenarios are considered for Scenario A (30% AVs; 30% CAVs; 15% AVs and 15% CAVs) and Scenario B (75% AVs; 75% CAVs; 37.5% AVs and 37.5% CAVs).

Induced Travel

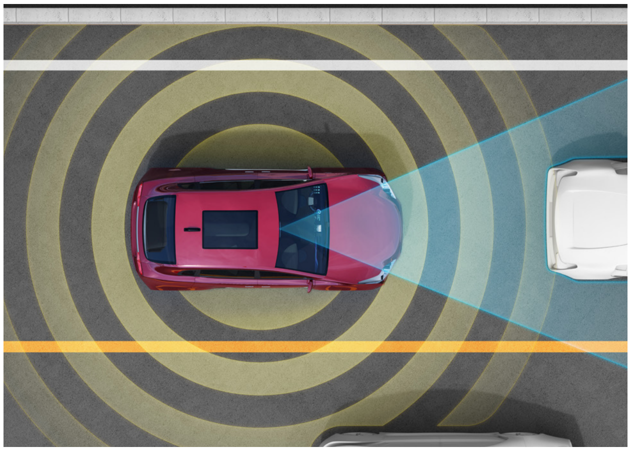
Self-driving vehicles are expected to improve mobility for current non-drivers, seniors, and individuals with disabilities. Truong et al. (2017) emphasized the potential of AVs and CAVs to cover the travel needs of 12-17 year old individuals who are currently dependent on public transport or their parents. A recently passed House Bill (HB 469) in North Carolina exempts operators of self-driving vehicles from the requirement to hold a driver's license and states that an adult is required only if a person under 12 years old is in the vehicle (NC General Assembly, 2017). Therefore, given the current NC legislation, new trips could be generated in the future by people as young as 12 years old. In addition, Wadud et al. (2016) suggested that there is a higher trip rate decrease after the age of 62, compared to the 44-62 age group, which may be due to impaired driving abilities. Based on these findings, we introduce a 30% increase in trip rates for the individuals between 12 and 17 years old and individuals who are 65 years old or older living in households assumed to own AVs or CAVs in Scenarios A and B. These changes are implemented for home-based other, non-home non-work, and home-based shopping trips for the aforementioned age groups. For individuals between 18 to 64 years old who have access to personal vehicles, it is assumed that their travel needs are already met (Wadud et al., 245 2016; Truong et al., 2017) and therefore, their trip rates remain unchanged. The TRM does not provide any information on individuals with disabilities; therefore, additional trips for this population group could not be incorporated into this analysis.

Highway Capacity Changes

The impact of AVs and CAVs on the capacity of freeway and highway segments operating without interruptions was assessed using state-of-the-art longitudinal and lateral movement models (Milan´es & Shladover, 2014; Xiao et al., 2017, 2018) introduced into SUMO, which is an open source simulation platform (Lopez et al., 2018). Several factors including maturity and reliability of associated technologies, liability aversion, and eminence are anticipated to result in AV decision algorithms that, on average, are more conservative compared to human driving, with negative implications on roadway capacity (Adebisi et al., 2020; Hasnat et al., 2021). On the other hand, CAVs will have the ability to communicate with other CAVs and the infrastructure and constantly track the environment. CAVs are therefore expected to maintain shorter time gaps between alike vehicle types and form platoons with short headways (Shladover et al., 2012; Tientrakool et al., 2011). Regarding the interactions of AVs, CAVs, and traditional vehicles in mixed-traffic conditions, they are modeled using a dynamic car-following algorithm that implements CAV car following (e.g., short time gaps and platooning) if a CAV follows another CAV, and AV car following (conservative time gaps and no platooning) if a CAV follows an AV or a traditional vehicle. The microsimulation results indicate that CAVs improve capacity at all levels of market penetration (Samandar et al., 2020). Specifically, a 4.7% increase in capacity is estimated for 30% MPR and a 36.1% increase for 75% MPR. However, 30% and 75% MPRs of AVs result in reduction of capacity by 4.9% and 7.8%, respectively (Samandar et al., 2020). These results are in line with previous research on CAVs (Shladover et al., 2012; Tientrakool et al., 2011) and recent studies on AVs (Adebisi et al., 2020; Bierstedt et al., 2014). For scenarios with a 50-50 mix of AVs and CAVs, the interactions between the different vehicle types in the traffic stream is found to result in small improvements in capacity even for high MPR (1.3% increase for 30% MPR and 3.3% increase for 75% MPR). These capacity changes are implemented on freeways and other uninterrupted highway segments in the TRM network.

Cluster Analysis

The results of the AV and CAV scenario analysis in the TRM are further evaluated using cluster analysis. This allows us to gain a better understanding of the spatial variation of network performance changes in the Triangle Region due to AVs and CAVs and their relationship with the built environment characteristics of each zone. We perform clustering for two types of travel time changes: (i) regional, based on the average travel time from each TAZ to all other TAZs, and (ii) local, based on the average travel time from each TAZ to the nearest ten TAZs. Travel time changes are estimated as the percentage change in travel time between an AV or CAV scenario and the base scenario for 2045. Other attributes included in the clustering are TAZ roadway density, freeway density, average travel distance to the three CBD areas in the Triangle Region, and percentage change in trips generated compared to the 2045 base scenario.



These features represent transportation supply and increased travel demand due to AVs or CAVs for each TAZ. We apply K-means clustering to partition TAZs into an optimal number of clusters by minimizing the clustering error (Wu, 2012; Lloyd, 1982). The clustering error is the sum of squared Euclidean distances between an observed TAZ attribute and the cluster mean for that attribute over all TAZs and attributes under consideration (Likas et al., 2003). The optimum number of clusters is determined based on the elbow method, which calculates the percentage of within cluster variance (distortion) for different numbers of clusters (Bholowalia & Kumar, 2014). The distortion scores in this study are calculated as the sum of squared distances from the centroid of each TAZ to the center of the cluster where the TAZ is assigned. Before applying the clustering algorithm, the TAZ attributes are rescaled so that their values are between zero and one; this is done to avoid estimation bias due to attributes with high variance (Choudhary et al., 2016; Han et al., 2012; Greenacre & Primicerio, 2013; Rokach & Maimon, 2008).

Predicting Households' Future Residential Location Choice

We are interested in understanding how changes in transportation network performance due to AVs and CAVs are going to impact households' residential location in the future. To this end, the explanatory variables in the residential location choice model are updated with the socioeconomic data for 2045 and the transportation-related outcomes from the TRM scenario analysis to produce residential location predictions for 2045. Using Halton sequencing, a vector of estimated coefficients $\hat{\beta}_h$ is drawn from the distributions of the individual coefficients of the Mixed MNL model. The coefficient vector $\hat{\beta}_h$ and the updated explanatory variables (zhi) are used to calculate the probability of household h choosing alternative TAZ i:

$$P_{hi} = \frac{e^{\hat{\beta}'_h z_{hi}}}{\sum_j e^{\hat{\beta}'_h z_{hj}}}$$

Equation 3.3

This process is repeated 1000 times for each household. In other words, for each household h, 1000 β $\hat{\beta}_h$ vectors are drawn using Halton sequencing; the individual probabilities are estimated using Eq. 3.3 and are averaged to provide an estimate of the average probability of choosing alternative i. For every household, the process is repeated for each of the 2819 TAZs in the study region. The TAZ with the maximum average probability value is reported as the chosen alternative for that household.

Summary of Findings

- Residential location decisions depend on transportation network performance
- Private CAVs increase the share of suburban and rural households by up to 7%
- Private, electric AVs lead to a 4% increase in suburban and rural households
- Conventional-fuel AVs do not notably impact the spatial distribution of households

3.5 Analysis of Household Residential Preferences in Triangle Region

Data Preparation

To model household residential location preferences, we use data from the 2016 Triangle Region Household Travel Survey. The survey was conducted between February and April 2016. A stratified random sample was used based on USPS delivery addresses with compensatory oversampling of low-income households, households with public transit users, zero-vehicle households, and households with college or university students, to ensure that the final responses would be representative of the household distribution in the region (RSG, 2016). A total of 76,097 households were invited through mail to participate in the survey; 4,194 households participated by completing a one-day travel diary for every member of the household. The survey included questions about household characteristics (number of adults, number of children, number of licensed drivers, income), vehicles (number, type), and occupation (location of primary and secondary work for workers, school location for students). The survey also asked for a one-day travel diary and contained other questions about travel characteristics. Out of the 4194 survey responses from households, 471 responses were removed because the home or work location was outside of the TRM region, no work location was provided, or multiple home locations were reported. From the remaining 3723 household responses, only 2435 households reported a home-based work trip; 97% of these households used personal vehicles to commute to work. The final dataset that we use for our analysis includes responses from 2356 households who live and work within the TRM region, and commute to work by personal vehicle. The households' home and work locations are geocoded in ArcGIS and spatially joined with the TAZ layer. A few zones (38 TAZs out of the 2857 TAZs) are excluded from the analysis because they do not contain any residential areas. These zones include recreational parks and protected green spaces, airports, university campuses, and shopping complexes. For the rest of the 2819 TAZs, land-use and built environment information such as number of commercial establishments, educational institutions, medical institutions, parks, tourist spots, and recreational establishments are collected from various NC GIS data libraries. Median house value for census block groups is available from the 2018 5-year estimates of the American Community Survey. This information is spatially joined with the TAZ layer in ArcGIS. Transportation system information (total and non-motorized roadway length), mean household income in each TAZ, and employment opportunities (retail jobs, industrial jobs, employment density) are available for 2013 through the Triangle CommunityViz 2.0 (CommunityViz, 2018).

Variable Description

Table 3.1 presents descriptive statistics for the variables considered in the analysis of residential location choice. The first part of the table focuses on built environment, land-use, and socioeconomic TAZ-level characteristics, while the second part of the table focuses on household information retrieved from the 2016 Triangle Region Household Travel Survey. The majority of the households in the survey sample have at least two working members, two or more vehicles, and live in owner-occupied single-family houses. Households' annual incomes are recorded within ten income brackets. The average (unweighted) household income in our sample is $50,970.

We estimate employment accessibility for TAZ i, Ai, to be proportional to the employment opportunities in all TAZs in the study region and inversely proportional to the travel time between TAZ i and all other TAZs:

$$A_i = \frac{1}{J} \sum_{j=1}^{J} \frac{Total\ Employment_j}{Travel\ Time_{ij}} \quad \text{Equation 3.4}$$

In addition, commute time and commute cost are estimated for each household. Commute time is the network travel time between TAZ centroids of a household's home and work location. A household's commute cost is estimated as the average vehicle operating cost for the distance travelled to work. Vehicle type information from the household responses is used to calculate the average operating cost per mile based on the American Automobile Association (AAA, 2018). For each household with multiple workers, commute time and distance to work are calculated as the total commute time and distance for all the workers in the household. As shown in Table 1, the sample's mean household commute time and cost is 27.89 minutes and $3.26, respectively.

Mixed Multinominal Logit Results and Discussion

The results of the Mixed MNL model are presented in Table 3.2. The model was estimated in STATA 15 using simulated log likelihood and 2000 Halton draws (Hole, 2007). Statistically insignificant parameters have been removed to reduce computational burden in the model estimation. Overall, the results are intuitive and consistent with our original hypotheses. We find that TAZs with higher population density, more

TAZ-level characteristics				
Variable	Mean	Standard deviation	Minimum	Maximum
TAZ area (square miles)	1.19	2.07	0.01	24.16
Population density, 2013 (1000 per square mile)	1.84	2.50	0.00	34.79
Percentage of White population, 2017	0.67	0.19	0.00	0.98
Percentage of African American population, 2017	0.22	0.18	0.00	0.85
Employment density, 2013 (1000 jobs per square mile)	2.55	14.65	0.00	499.32
Employment accessibility, 2013	15.24	3.95	6.13	23.39
Roadway density, 2013 (roadway miles per sq. miles of area)	13.21	9.80	0.00	72.98
Non-motorized path length, 2013 (miles)	1.21	2.09	0.00	37.16
Number of educational institutions, 2018	0.79	1.27	0.00	11.00
Number of medical facilities, 2016	0.17	0.59	0.00	7.00
Number of recreational centers, 2016	0.12	0.39	0.00	7.00
Number of religious institutions, 2016	0.78	1.20	0.00	9.00
Number of government offices, 2016	0.39	1.46	0.00	25.00
Number of libraries and museums, 2016	0.13	0.50	0.00	7.00
Crime index, 2017 (number of violent crimes per 100,000 population)	267.24	99.95	175.89	461.86
Mean household income, 2013 (1000 USD)	75.04	36.24	32.80	302.94
Median house value, 2018 (in 1000 USD)	251.01	103.30	63.90	699.31
Household characteristics (unweighted), 2016 Triangle Region Household Travel Survey				
	0	1	2	3 or more
Household size	-	21%	39.5%	39.5%
Number of adults	-	24.2%	66.6%	9.2%
Number of children	64.7%	16.1%	14.4%	4.8%
Number of students	57.9%	20.3%	15.9%	5.9%
Number of workers	-	45.7%	50.3%	4.0%
Number of vehicles	0.0%	27.5%	52.0%	20.5%
Number of bikes	41.0%	18.3%	18.6%	22.1%
Household members with a driver's license	0.0%	26.4%	64.4%	9.2%
Home ownership	owned 77.2%	rented 21.1%	other 0.4%	unspecified 1.3%
Life cycle	working with children 34.3%	retirees without children 8.1%	retirees with children 1.0%	working without children 56.6%
Resident type	single-family house 74.0%	town house 10.5%	building with ≥ 2 units 15.0%	other 0.5%
Residence area type	CBD 0.3%	Urban 44.5%	Suburban 38.6%	Rural 16.6%
	Mean	Standard deviation	Minimum	Maximum
Household annual income, 2016 (1000 USD)	101.98	59.32	7.5	300.00
Household commute time, 2016 (minutes)	26.57	16.65	3.00	116.06
Household commute cost, 2016 (USD)	3.12	2.61	0.02	17.47

Table 3.1: Summary statistics of TAZ and household characteristics.

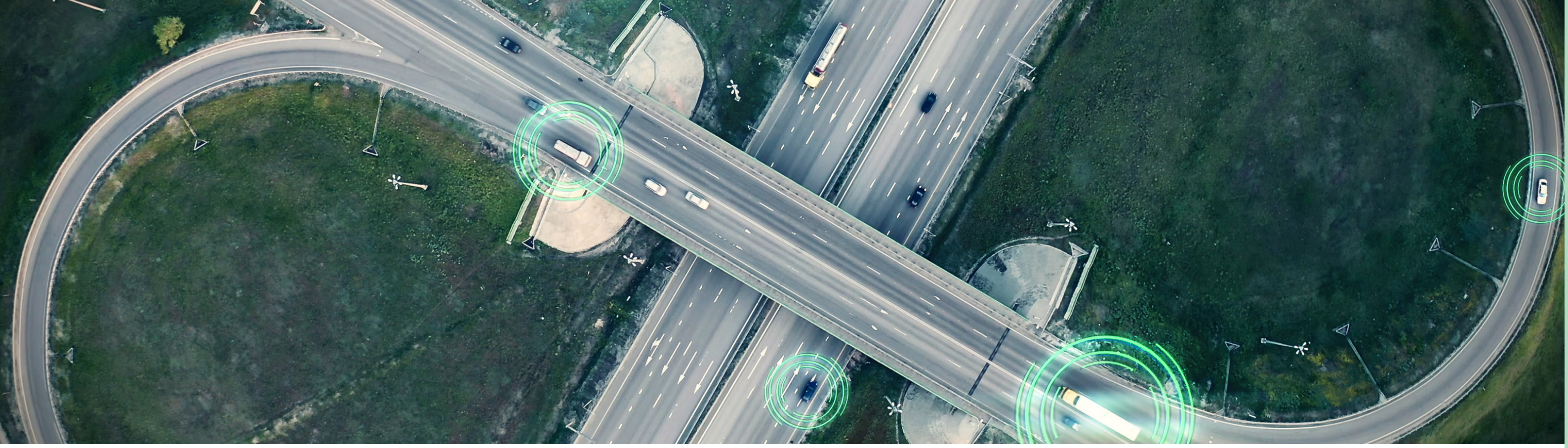
Variable	Estimated Parameter	Standard Deviation of Parameter Distribution
TAZ-level characteristics		
Population density	0.1052 (0.0095)***	—
Employment density	-0.2108 (0.0185)***	0.0812 (0.0146)***
Roadway density	-0.0363 (0.0046)***	—
TAZ area	0.1410 (0.0136)***	—
Number of medical facilities	0.0868 (0.0359)*	—
Number of recreational facilities	0.1985 (0.0461)**	—
Crime index	-0.0008 (0.0003)*	—
Urban TAZ indicator	1.3207 (0.1109)***	—
Suburban TAZ indicator	1.0892 (0.0864)***	—
TAZ-level characteristics interacted with household demographics		
Absolute difference in household income and TAZ-level mean household income	-0.0121 (0.0008)***	—
Median house value / Household Income	-0.0402 (0.0144)**	—
White household × Percentage of White population in TAZ	2.8543 (0.1917)***	—
African American household × Percentage of African American population in TAZ	6.5548 (0.4413)***	—
Household with student member × Number of educational institutions in TAZ	0.1795 (0.0282)***	—
Household with more vehicles than adults × Distance to closest CBD	0.0546 (0.0081)***	—
Household with at least 2 bicycles × TAZ non-motorized path length	0.0881 (0.0096)***	—
Commuting and accessibility		
Household commute time	-0.1000 (0.0047)***	0.0431 (0.0037)***
Household commute cost / (Household income / Average household income)	-0.0789 (0.0164)***	0.0547 (0.0153)***
Employment accessibility	-0.1271 (0.0110)***	—
Number of households	2356	
Log-likelihood at zero	-6339.88	
Log-likelihood at convergence	-6261.77	

***ρ <0.001, **ρ <0.005, *ρ <0.05

Table 3.2: Mixed multinomial logit estimation results for household residential location choice (random parameters are normally distributed; standard errors are in parentheses).

medical and recreational facilities, lower road density, and lower crime index have a higher probability of being chosen by a household, on average. In addition, our results suggest that household preferences are heterogeneous with respect to TAZ employment density. The estimated coefficient of employment density is normally distributed with a mean of -0.2108 and standard deviation of 0.0812, indicating that for 99.5% of cases, higher employment density reduces the probability of choosing a TAZ for residential location. Furthermore, the results indicate that households of similar income and racial composition tend to be spatially concentrated. This outcome, which has also been reported by previous studies (Pinjari et al., 2009; Waddell, 1992), is associated with housing affordability considerations as well as the residential segregation that persists in many US regions. Households that include students are more likely to choose TAZs with higher number of educational institutions, all else being equal. Additionally, we find that households with a higher number of vehicles tend to live farther from CBD areas, and households that own at least two bicycles tend to reside in areas with more non-motorized paths. The positive coefficients for the indicator variables representing urban and suburban TAZs provide evidence of stronger preference for urban and suburban living.

Our results confirm that the travel time between home and work plays an important role in a household's residential location choice. Higher commute time is associated with lower probability of a TAZ being selected as home location. In line with previous research (Guo & Bhat, 2007; Pinjari et al., 2011), we also find that the effect of commute time varies among households. Household commute time and cost are highly correlated because commute cost is directly proportional to commute distance. To avoid a multicollinearity problem and to account for variability in cost sensitivity across households, we divide the household commute cost by the household relative income (household income divided by the sample average household income). As expected, we find that on average, household commute cost is negatively associated with a location's utility. Last, our results indicate that higher employment accessibility reduces the probability of a TAZ being selected, restating the common preference for residential areas farther from employment centers for households in the Triangle Region.



3.6 Network-Level Impacts of AV and CAV Adoption

The TRM model was run for (i) a base scenario, which provides the baseline results on system performance considering zero AV or CAV adoption for the year 2045, (ii) three scenarios (A1, A2, A3) that assume 30% MPR of AVs or CAVs, and (iii) three scenarios (B1, B2, B3) that assume 75% MPR of AVs or CAVs (Table 3.3). All AV and CAV scenarios incorporate induced travel demand (discussed in Section 4.2.3) and changes in multi-lane highway and freeway segments' capacity (discussed in Section 4.2.4). The daily vehicle-miles traveled (VMT), average peak-period freeway speed, daily hours of delay, and average travel time for trips to work for the TRM network are presented by scenario and compared with the base 2045 scenario in Table 3.3.

Overall, the average changes estimated for daily VMT and average commute time compared to the base scenario are relatively small and less than 3%. For average peak-period freeway speed and daily hours of delay, the estimated changes are more substantial but still below 15% of the

Table 3.3: Network-level impacts of AV and CAV adoption.

Market Penetration rate scenarios	% Change in capacity	Vehicle miles traveled (VMT)		Peak-period freeway speed		Hours of delay		Travel time: trips to work	
		Value (million)	%Change	Value (mph)	%Change	Value	%Change	Value (min)	%Change
Base scenario	-	90.79	-	52.7	-	451,335	-	25.84	-
(A1) 30% AV	4.90	91.77	1.07	51.5	-2.28	489,239	8.40	26.29	1.74
(A2) 30% CAV	4.70	92.00	1.33	53.3	1.14	453,353	0.45	25.80	-0.15
(A3) 15% AV, 15% CAV	1.30	91.92	1.23	52.7	0.00	465,011	3.03	25.97	0.50
(B1) 75% AV	7.80	92.40	1.77	50.8	-3.61	518,732	14.93	26.63	3.06
(B2) 75% CAV	36.10	92.95	2.38	57.0	8.16	401,669	-11.00	25.09	-2.90
(B3) 37.5% AV, 37.5% CAV	3.30	92.69	2.09	52.9	0.38	473,116	4.83	26.02	0.70

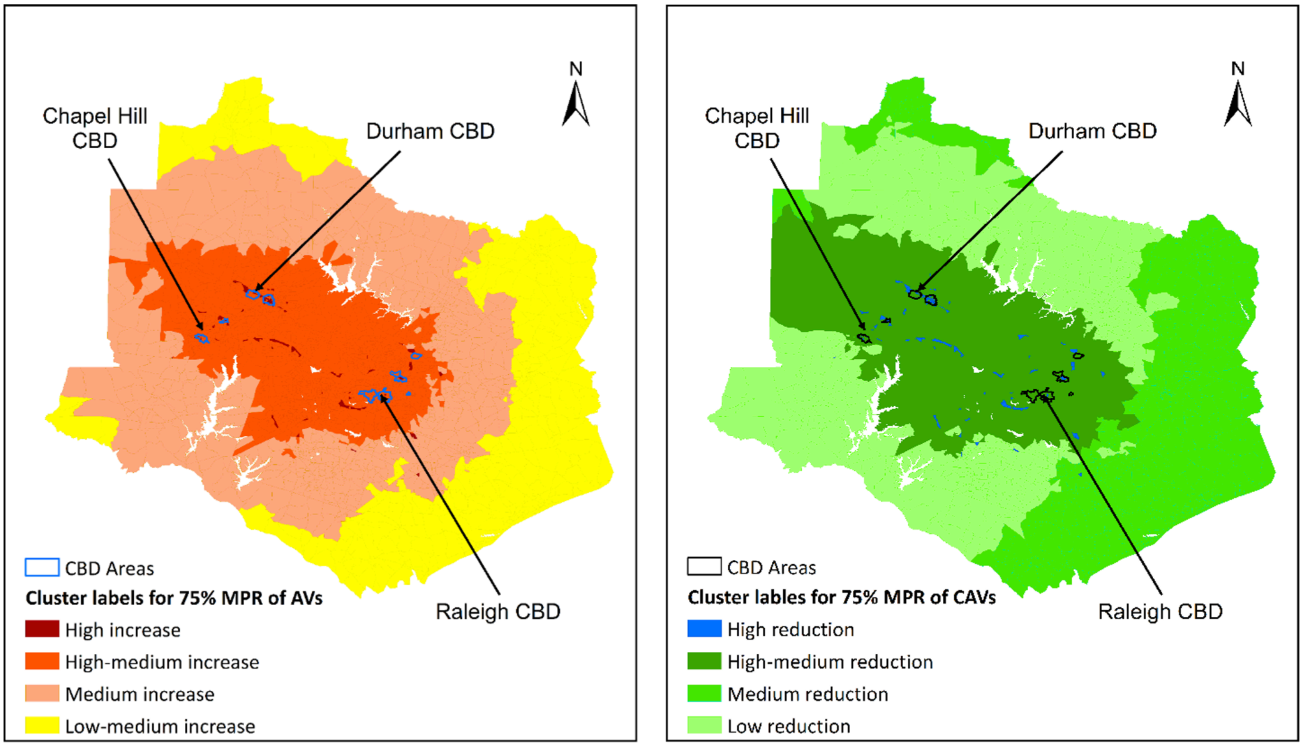
Cluster name (number of TAZs)	% Change in travel time*	Roadway density (miles/sq. mile)	Freeway density (miles/sq. mile)	Average distance from CBDs (miles)	% Change in trips generated
75% MPR of AVs					
High increase (136)	3.62	73.58	26.20	16.70	2.27
High-medium increase (1665)	3.15	15.32	2.03	18.50	2.45
Medium increase (705)	2.70	7.84	0.58	30.44	2.66
Low-medium increase (351)	2.33	6.16	0.33	46.43	2.55
75% MPR of CAVs					
High reduction (147)	-4.06	71.78	24.69	16.82	2.28
High-medium reduction (1769)	-4.00	14.69	1.97	19.13	2.53
Medium reduction (422)	-3.35	7.05	0.48	44.62	2.49
Low reduction (519)	-1.72	7.11	0.28	30.22	2.67

Table 3.4: K-mean clustering results - Regional travel time changes in2045. Normally distributed; standard errors are in parentheses.

base scenario. We find an increase in VMT for all scenarios. This change in VMT is greater for higher market penetration of privately-owned AVs and CAVs. In terms of network performance, results indicate substantial differences between adoption of AVs and CAVs. Scenarios representing AV-only adoption (A1 and B1) lead to lower speed and higher delays and travel time, while the opposite holds for scenarios of CAV-only adoption (A2 and B2). Scenarios that simulate a mixture of AVs and CAVs (A3 and B3) are associated with small network-level changes which range between 0% and 4.8%. Focusing on the most impactful scenarios, a 75% MPR of AVs is expected to lead to deteriorated network performance (14.93% increase in daily hours of delay and 3.61% decrease in peak-period freeway speed), while a 75% MPR of CAVs is expected to decrease daily hours of delay by 11% and increase peak-period freeway speed by 8.16% on average.

We use K-means clustering to explore how the changes in network performance vary with transportation supply, demand, and other zone attributes. Network performance changes are captured by TAZ-to-TAZ travel time. We calculate the percentage change in average travel time from each TAZ to all other TAZs compared to the base scenario to capture average regional network performance changes. We also calculate the percentage change in average travel time from each TAZ to the nearest ten TAZs compared to the base scenario to capture the changes in local network performance. Average regional travel time decreases (compared to the base scenario) only for the scenarios of CAV adoption (A2 and B2). Average local travel time increases for all scenarios, with a small decrease for the scenario of 75% MPR of CAVs (B2). The cluster analysis includes four additional TAZ attributes for 2045: roadway density, freeway density, average distance to the three CBD areas in the Triangle Region, and percentage change in total trips generated compared to the base scenario. For both regional and local analyses, the optimum number of clusters is found to be four.

Table 3.4 and Figure 3.2 present the results of the regional cluster analysis for 75% MPR of AVs and 75% MPR of CAVs (scenarios B1



(a) 75% MPR of AVs (b) 75% MPR of CAVs

Figure 3.2: K-means clustering results - Regional travel time changes in 2045.

Cluster name (number of TAZs)	% Change in travel time*	Roadway density (miles/sq. mile)	Freeway density (miles/sq. mile)	Average distance from CBDs (miles)	% Change in trips generated
75% MPR of AVs					
High increase (449)	1.52	13.40	3.7	21.59	2.48
Medium increase (1356)	0.45	21.68	3.86	17.29	2.43
Low-medium increase (668)	0.35	7.85	0.69	30.10	2.64
Low increase (384)	0.14	6.64	0.26	45.80	2.47
75% MPR of CAVs					
Medium increase (491)	0.03	6.85	0.32	43.78	2.48
Low reduction (171)	-0.004	68.42	20.85	17.11	2.28
Medium reduction (1386)	-0.05	15.45	2.15	17.54	2.51
High reduction (809)	-0.44	8.26	0.94	27.31	2.67

Table 3.5: K-means clustering results - Local travel time changes in 2045.

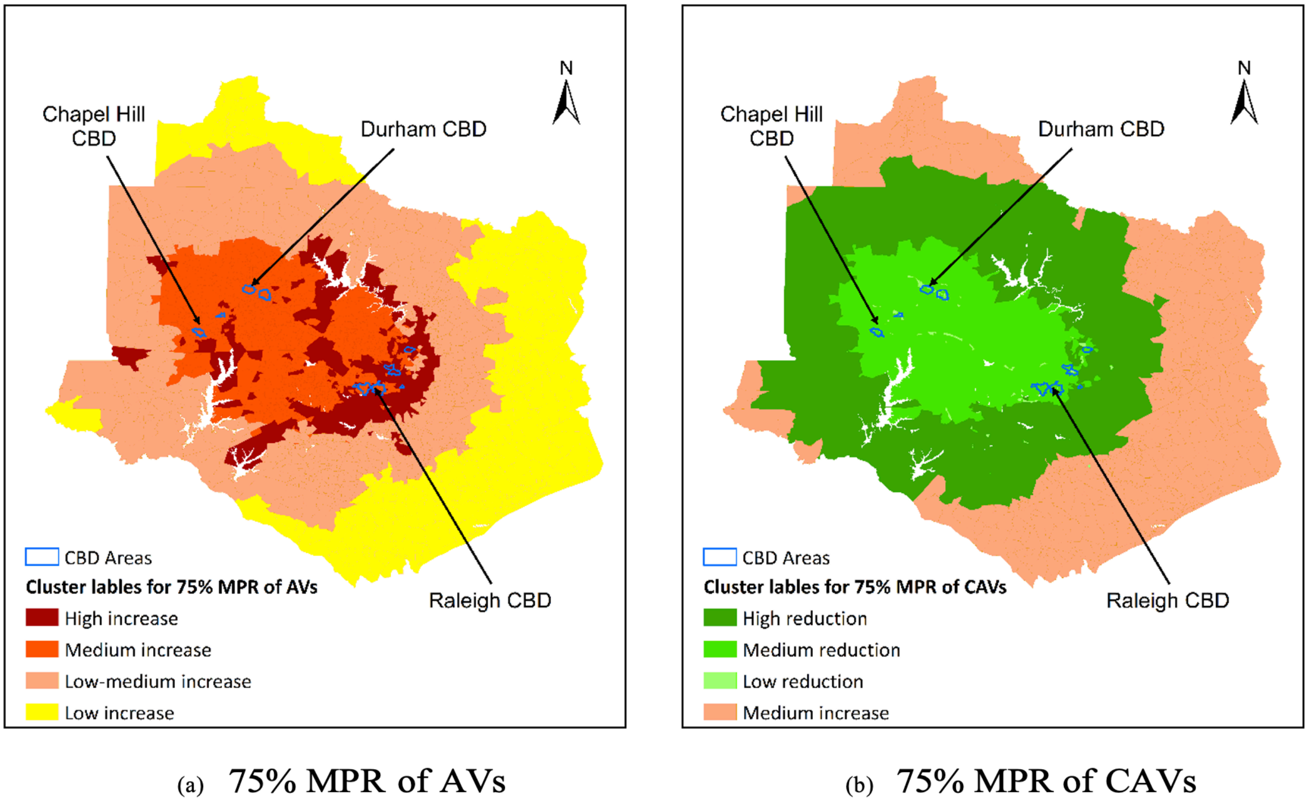


Figure 3.3: K-means clustering results - Local travel time changes in 2045.

and B2). The results are consistent for the rest of the scenarios, but the magnitude of the network performance changes is much smaller. The clusters are named based on the level of travel time changes for the TAZs within each cluster. For 75% MPR of AVs, TAZs in the "High increase" cluster experience an average regional travel time increase of 3.62%. These TAZs are mainly located in CBD areas or other areas close to the CBD with high roadway and freeway density. As we move further away from the CBD areas, the regional travel time impacts decrease. TAZs within the "Low-medium increase" cluster have an average regional travel time increase of 2.33% and are located along the peripheral zones, mainly in rural areas with low roadway and freeway density. For 75% MPR of CAVs, all four clusters experience a reduction in average travel time compared to the base scenario. TAZs in the "High reduction" cluster experience an average regional travel time decrease of 4.06%. These TAZs are located in CBD areas and other urban or suburban areas with high roadway and freeway density. The cluster with the smallest travel time improvements includes TAZs primarily located in the east portion of the Triangle Region and has the lowest average roadway and freeway density compared to the other clusters.

Different results are found for the cluster analysis related to local network performance changes, as shown in Table 3.5 and Figure 3.3. For 75% MPR of AVs, TAZs within the "High increase" cluster experience a 1.52% average increase in local travel time and are mainly located along the urban fringe, whereas "Medium increase" TAZs are primarily in urban areas closer to the CBD and have the highest average roadway and freeway density compared to other clusters.

Smaller local travel time changes are found for the majority of suburban and rural TAZs with lower road and freeway densities. On the other hand, for 75% MPR of CAVs, the majority of TAZs experience a decrease in local travel time. The highest reduction is primarily observed in suburban and rural areas with low roadway and freeway density, while very small reductions in local travel time are found for urban and CBD areas with higher roadway and freeway density. Even though this result seems counterintuitive, it can be explained through the consideration of network effects in traffic assignment: Because of the increase in capacity of freeway and certain highway segments due to CAV adoption, more traffic is diverted to these facilities creating local traffic nearby and reducing traffic elsewhere. Lastly, local travel times are found to increase for some TAZs located mainly in rural and outer suburban areas of the Triangle Region.

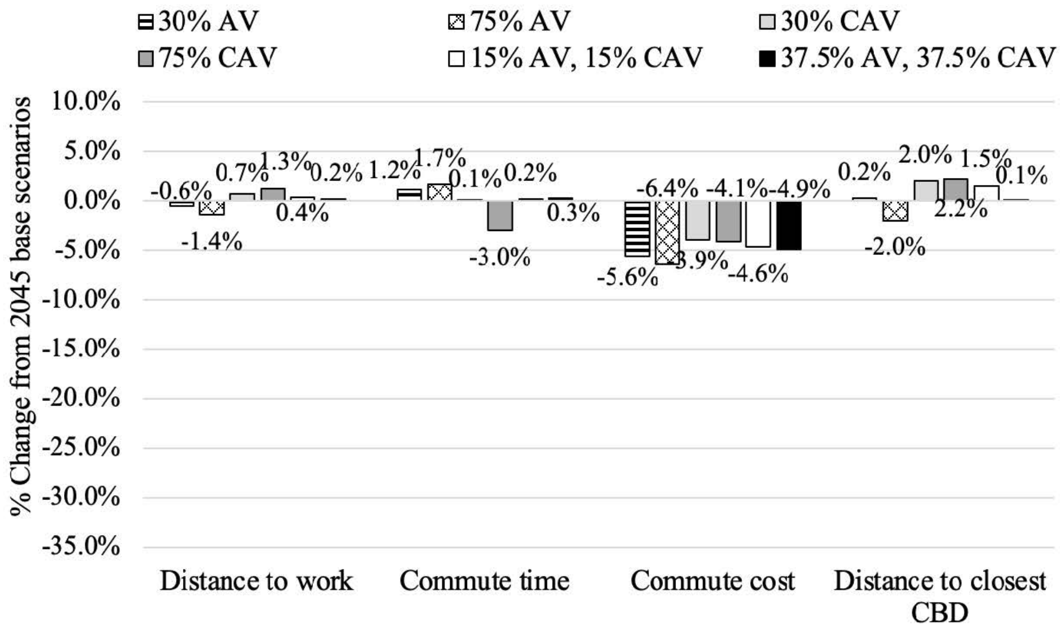
3.7 Changes in Household Residential Location in 2045 Under AV and CAV Adoption Scenarios

Future residential location choices are predicted for the 2045 base scenario as well as for the six AV and CAV scenarios for households that commute to work by personal vehicle. These predictions are carried out by applying the estimated Mixed MNL model using updated variable values that reflect 2045 conditions based on the methodology described in Section 4.3. TAZ-level characteristics, including population density, employment density, mean household income, roadway density, and non-motorized path length are updated for 2045 using the information available from the Triangle CommunityViz 2.0. Employment accessibility and household commute time and cost are estimated for 2045 based on the TAZ-to-TAZ TRM results for each scenario. We assume that all households in the survey sample, irrespective of AV/CAV ownership, experience the same travel time for a given origin-destination pair and a given scenario because the travel times reflect network-level conditions. Commute costs differ by type of vehicle though. Previous research has suggested that self-driving vehicles will have a lower operating cost than human driven vehicles, due to more balanced driving and lower insurance rates (Millard-Ball, 2019; B¨osch et al., 2018; Stephens et al., 2016). The reduction in the operating cost is expected to vary by roadway facility type and fuel type (Stephens et al., 2016). Estimates of vehicle operating cost reduction differ by study, but overall, previous research has suggested an average 5% decrease in the operating cost of conventional-fuel self-driving vehicles and 33% decrease in the operating cost of electric self-driving vehicles, compared to conventional-fuel human driven vehicles (Millard-Ball, 2019; B¨osch et al., 2018; Stephens et al., 2016). These operating cost reductions are adopted herein for the households with AVs or CAVs. Operating cost differences between AVs and CAVs have not been reported in the literature yet.

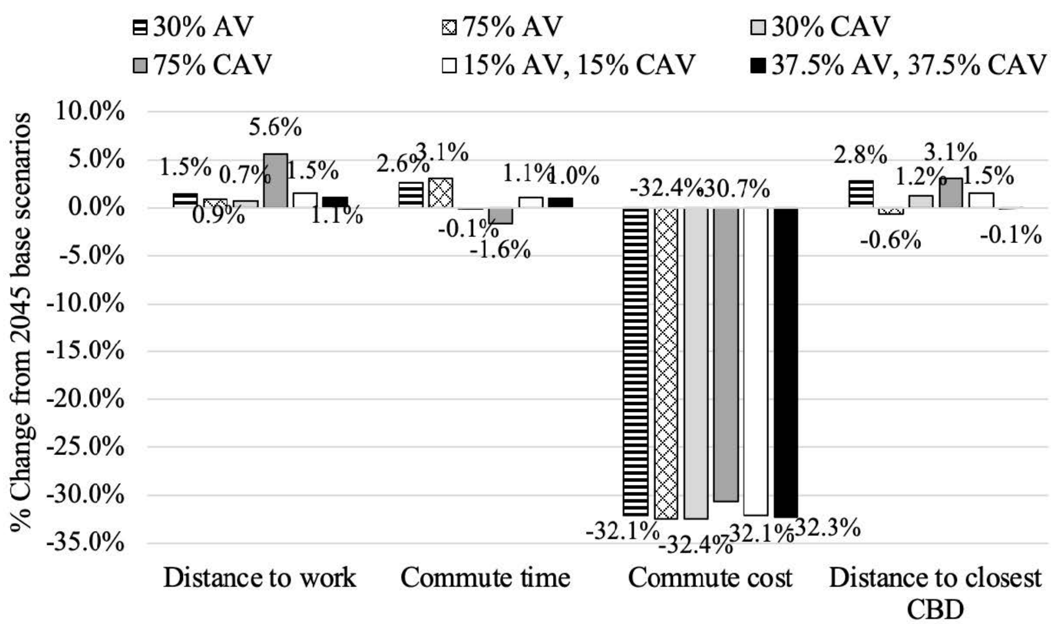
We note that the analysis discussed in Section 6 includes all zones and households in our study area to forecast network conditions, while the household survey sample used here (as well as in Section 5) contains only households who commute to work by personal vehicle. Although our analysis is restricted to this group of households, we use the survey weights so that our results are representative of the Triangle Region's working households with personal vehicles. The weight of each survey record is based on household size, number of workers, number of vehicles, age of the head of the household, income, and number of children in the household to match the demographic data targets from the 2010–2014 five-year estimates of the American Community Survey (RSG, 2016). In addition, out of the 2356 household survey records whose behavior was analyzed in Section 5, 1452 (unweighted) households qualify for AV or CAV ownership under Scenario A (30% market penetration) and 2210 (unweighted) households qualify under Scenario B (75% market penetration). We first focus on the changes of commute and location characteristics of these households, and then we present the overall results of residential location for all working households who drive to work.

Figure 3.4 presents the changes in location and commute characteristics by scenario for households with conventional-fuel and electric AVs and CAVs. These results constitute percentage changes of weighted averages between an AV/CAV scenario and the respective 2045 base scenario. We find that extensive adoption of conventional-fuel AVs leads to households choosing home locations closer to their work (0.6% and 1.4% decrease in average commute distance for 30% and 75% MPR of AVs, respectively, compared to the base scenario) in order to counteract the deteriorated transportation network conditions. Despite the decrease in distance between home and work, commute time rises, reflecting the negative impact of AVs' market penetration on network speeds and delays. In the case of electric AVs, the effect of lower vehicle operating cost on households' utility outweighs the impact of higher network travel times resulting in households moving farther from work and a 2.6%-3.1% increase in commute time, on average. On the other hand, scenarios of CAV adoption lead to households, on average, choosing to reside further away from work and CBD areas compared to the 2045 base scenario. The increase in the average distance between home and work is partially motivated by the network performance improvements due to widespread CAV adoption. The average household commute time reduces by 3.0% for a 75% market share of conventional-fuel CAVs despite the increase in commute distance, due to the improved regional and local network conditions. Regarding electric CAVs, the

decrease in vehicle operating cost reduces the disutility of longer commutes even further and leads to more substantial changes in average commute distance and the households' distance from the CBD areas. Overall, the results indicate that the market penetration of CAVs enables the average household to choose a more attractive residential location in terms of amenities and neighborhood characteristics and even enjoy



(a) Conventional-fuel AVs and CAVs



(b) Electric AVs and CAVs

Figure 3.4: Average changes in location and commute characteristics of households with AVs/CAVs compared to the respective 2045 base scenario. 2045 base scenario weighted averages for 30% market penetration (1452 survey records): distance to work = 24.87 miles; commute time = 45.43 minutes; commute cost = $4.63; distance to closest CBD = 7.46 miles. 2045 base scenario weighted averages for 75% market penetration (2210 survey records): distance to work = 20.75 miles; commute time = 39.15 minutes; commute cost = $x3.87; distance to closest CBD = 8.13 miles.

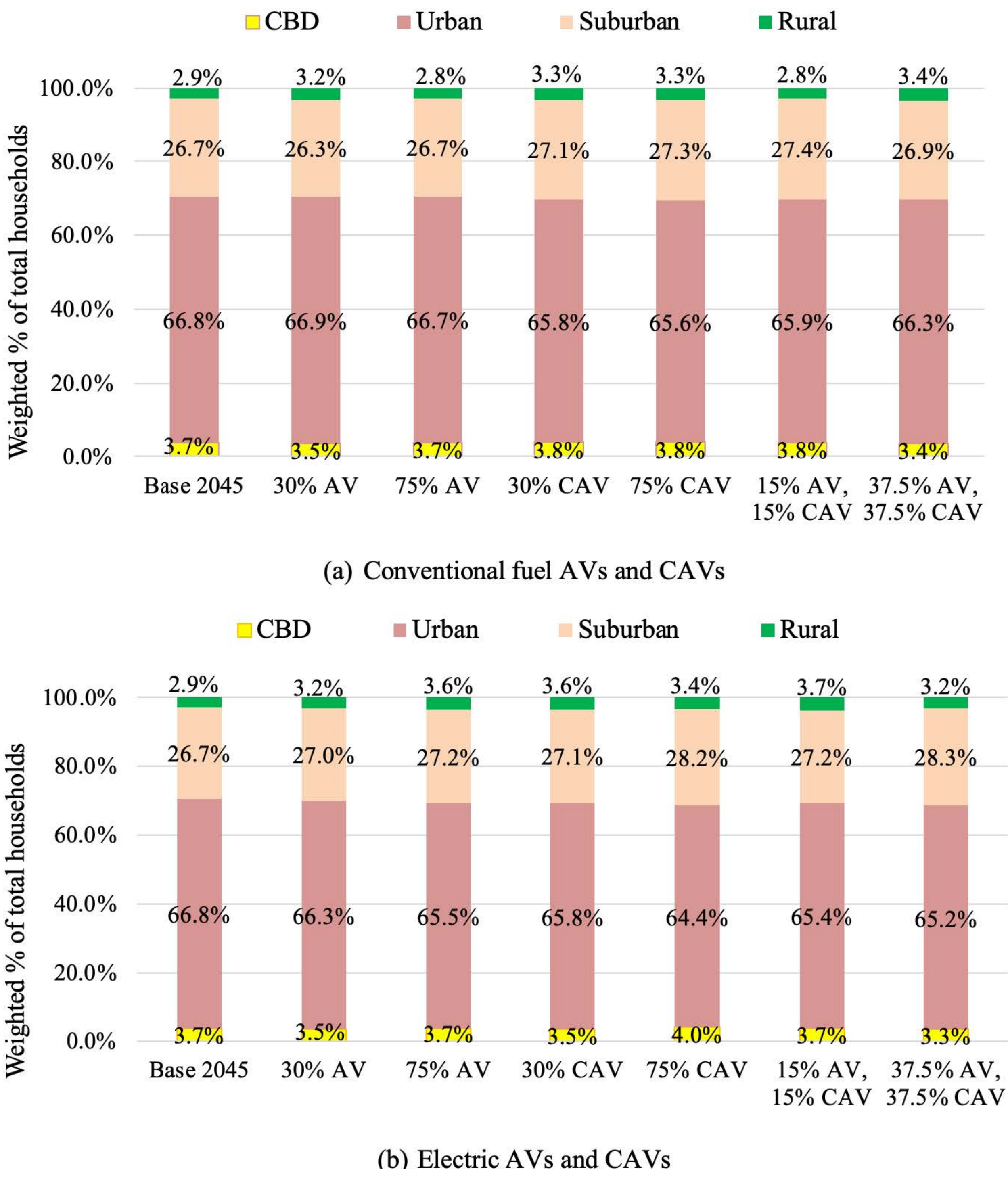
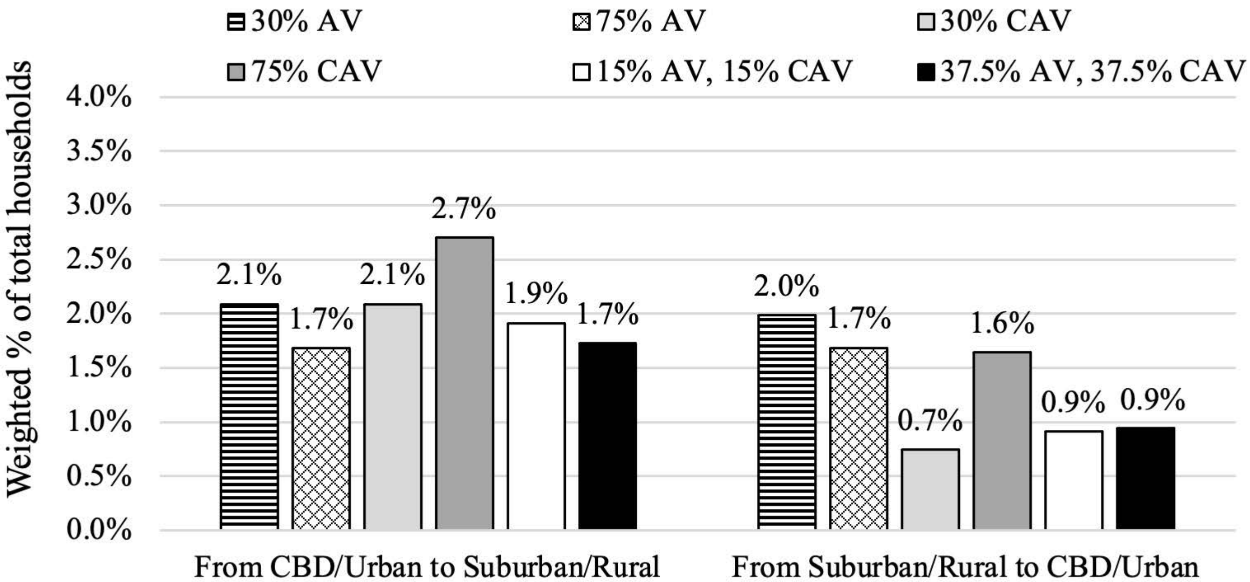
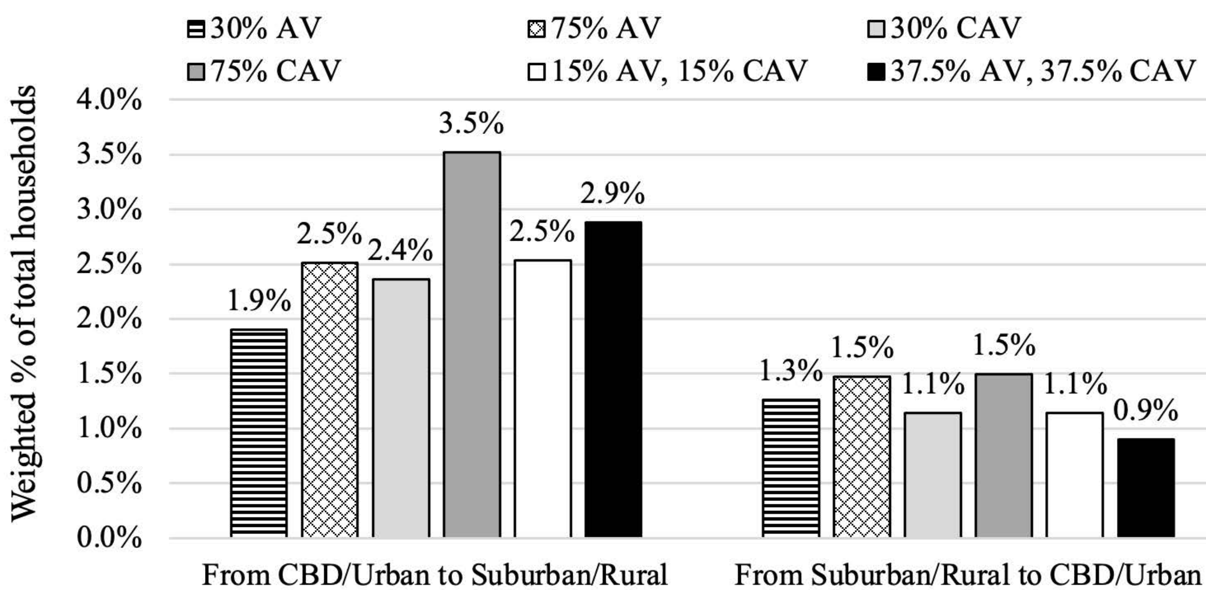


Figure 3.5: Predicted residential location of households that commute to work by personal vehicle.



(a) Conventional-fuel AVs and CAVs



(b) Electric AVs and CAVs

Figure 3.6: Predicted residential location shifts between the 2045 base scenario and AV/CAV scenarios for households that commute to work by personal vehicle.

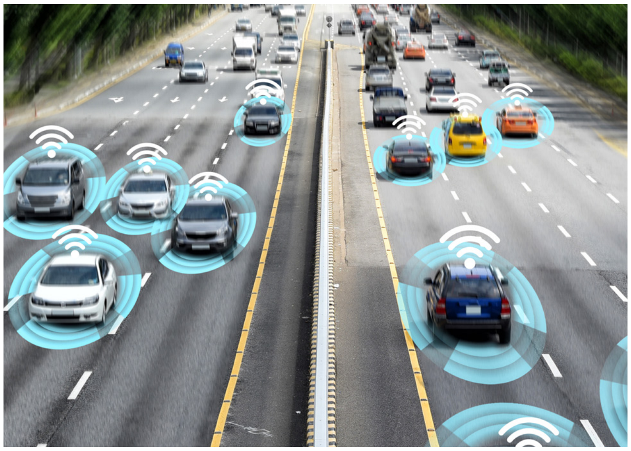
a small decrease in commute time despite the greater commute distance compared to the base scenario. As shown in Section 6, when there is a mixture of AVs, CAVs, and traditional vehicles in the traffic stream the positive impacts of CAVs on the transportation network are relatively counterbalanced by the negative AV effects, leading to small overall changes. Moderate impacts in household location are found for these scenarios mainly for the case of electric vehicles, primarily driven by the decrease in vehicle operating costs.

The choices of households with traditional vehicles may also be affected given the predicted impacts of vehicle automation and connectivity on the transportation system performance. It is therefore important to study the overall impacts of these technologies on the spatial distribution of households within the study region. The CBD, urban, and suburban areas within the Triangle Region are predicted to grow substantially by 2045 (Figure 3.1). Compared to 2013, our model predicts more households located in urban and CBD areas by 2045. Figure 3.5 presents the predicted location of households who commute to work by personal vehicle (weighted proportion of households) for the 2045 base scenario and the AV/CAV scenarios. The results show that the adoption of conventional-fuel AVs has no notable impacts on the distribution of households in the Triangle Region. However, conventional-fuel CAVs lead to a higher proportion of households in suburban and rural areas (up to 1.0 percentage points higher compared to the base scenario). In the case of electric vehicles, the reduced operating cost outweighs the influence of other variables and results in changes towards the same direction for all scenarios: a larger proportion of households would choose to reside in suburban and rural areas than in urban areas, compared to the base scenario. The suburbanization trends are stronger for CAV scenarios though. For example, electric AV adoption decreases the share of urban households by up to 1.3 percentage points while an up to 2.4 percentage point reduction is found for electric CAVs.

We note that the residential location choice of each household is a complex decision arising from the consideration of multiple factors as well as random variation (Table 3.2). The widespread adoption of AVs and CAVs translates into distinctive regional and local network impacts, which may affect households differently depending on their job location and socioeconomic and other attributes. This is demonstrated in Figure 6. It is shown that, for example, 1.9% of households that were predicted to reside in CBD or urban areas in 2045 chose a suburban or rural area when a 30% MPR of electric AVs was assumed; at the same time, 1.3% of households that were predicted to reside in suburban or rural areas in 2045 chose a CBD or urban area when a 30% MPR of electric AVs was assumed. This result indicates that there is variation among household decisions but the net difference, which is reflected in Figure 3.5, suggests a suburbanization trend. Figure 3.6 also reveals that only a small number of households (up to 3.5%) is predicted to choose a different area type between the 2045 base scenario and any AV or CAV scenario.

3.8 Conclusion

Mass adoption of self-driving vehicle technologies is expected to significantly impact transportation system performance and mobility, which are vital factors of residential location decisions for households. This study investigates and compares the long-term effects of moderate to high market penetration rates of personal AVs and CAVs on the distribution of households within a metropolitan area. First, this study estimates a Mixed Multinomial Logit model to capture the existing residential location choice preferences of households living in the Triangle Region of North Carolina and commuting to work by personal vehicle. Then, the region's transportation network performance for several AV and CAV-related scenarios for the year 2045 is simulated using the Triangle Region four-step travel demand model. The outputs from the travel demand model along with predicted sociodemographic variables for 2045 are used to forecast the future residential location of the studied household population by AV and CAV scenario. The analysis encompasses a wide range of scenarios, including conservative and optimistic levels of market penetration, self-driving vehicles with and without vehicle connectivity components, and fuel types associated with different operating costs, providing a broader spectrum of the potential effects of driverless vehicle technologies.



High market penetration of AVs is characterized by reduced highway capacity, which adversely impacts transportation network speeds, travel time, and delays. Specifically, a 75% MPR of AVs is associated with a 14.93% increase in daily hours of delay and 3.61% decrease in peak-period freeway speed. In addition, a higher rise in average travel time from each TAZ to all other TAZs is experienced in CBD and urban areas with higher road and freeway density. Locally, the travel times are higher around the urban fringe, while a medium increase is found within urban areas. For moderate to high market penetration of conventionalfuel AVs, households tend to reside closer to work to partially offset the degraded transportation network conditions, but the changes are small and do not significantly affect the distribution of households within the Triangle Region. On the other hand, the substantial reduction in the operating cost in the case of electric AVs is found to outweigh the negative impacts of reduced network performance. Our results indicate that extensive adoption of electric AVs is associated with up to a 1.3 percentage point decrease in the share of households residing in urban areas compared to the 2045 base scenario. This translates to a 2% decrease in urban households that commute to work by personal vehicle.

Adoption of CAVs is expected to enhance highway throughput compared to AVs and human driven vehicles. We show that a moderate to high market penetration of CAVs will improve the overall transportation network performance. The cluster analysis for regional network performance changes suggests higher reductions in average travel time from each TAZ to all other TAZs in CBD and urban areas that have higher roadway and freeway density. Local travel times also decrease, with the highest reductions in suburban and rural areas with low roadway and freeway density. These conditions motivate households to reside further away from their work location in search of more preferable neighborhood amenities and other characteristics without increasing their commute time compared to the 2045 base scenario. For a 75% MPR of electric CAVs, the average commute distance of households with personal CAVs increases by 5.6% compared to the 2045 base scenario. This leads to a 2.0 percentage point increase in the share of households residing in suburban or rural areas within the Triangle Region. This suburbanization trend constitutes the highest impact identified in this study. It reflects an approximately 7% increase in this region's suburban and rural population who commutes by personal vehicle through shifts from urban zones.

Some additional conclusions that may be relevant to practitioners are discussed herein. First, it is important to note that given a transportation network where there are no dedicated lanes for AVs or CAVs in the majority of the roadway segments, the improved or deteriorated network conditions due to mixed traffic will be experienced by all commuters and may lead to different location decisions even for households that do not own AVs or CAVs. Second, our study suggests substantial impacts mainly for high market penetration of self-driving technologies in combination with vehicle electrification. Therefore, it is likely that it will take more than three decades to realize such impacts. Simultaneously, public agencies should carefully consider the forecasted suburbanization trends and promptly explore policies, programs, and investments that discourage private vehicle ownership.

This research makes an essential contribution by predicting a range of long-term changes in the distribution of a large population group (adults who commute to work by personal vehicle) within a US metropolitan area given various scenarios. This work also contributes to the so far limited understanding of the differential impacts of AVs and CAVs. This study's results can be used by transportation and planning agencies to update local or regional plans, or as scenarios in their own analyses. Other regions could also adopt our methodology to produce region-specific estimates.

There are several limitations related to this research. First, our analysis focuses only on households with at least one working member who use their personal vehicles to commute to work and both their home and work location are within the Triangle Regional Model region (Figure 3.1). This population represents approximately 60% of the total households in the Triangle Region. However, we note that this constitutes a good representation of the working households in the region because most working households not included in the analysis were removed due to their work or home location being outside the TRM region. Less than 4% of working households commute to work by other transportation modes in the Triangle Region. In addition, the mixed MNL predictions for 2045 (Section 3.7) ignore some supply-side considerations, including the availability of residential units in different TAZs. This does not hold for the 2045 network-level analysis results (Section 3.6) because those are based on population and land-use characteristics for 2045 incorporated in the TRM from the Triangle Community Viz 2.0. Nevertheless, this is not considered a substantial limitation because of the small population shifts forecasted for most scenarios. Lastly, this study focuses solely on privately owned vehicles and commute to work. Future research should consider the impacts of shared AV and CAV services as well as other trip types and non-working households to provide a more complete picture of the anticipated changes.

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