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# An Assessment of Autonomous Vehicles: Traffic Impacts and Infrastructure Needs—Final Report

Dr. Kara Kockelman (Research Supervisor)
with Dr. Stephen Boyles, Dr. Peter Stone, Dr. Dan Fagnant, Rahul Patel, Michael W. Levin, Dr. Guni Sharon, Michele Simoni, Dr. Michael Albert, Hagen Fritz, Rebecca Hutchinson, Prateek Bansal, Gleb Domnenko, Pavle Bujanovic, Bumsik Kim, Elham Pourrahmani, Sudesh Agrawal, Tianxin Li, Josiah Hanna, Aqshems Nichols & Dr. Jia Li

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16. Abstract

The project began by understanding the current state of practice and trends. NHTSA's four-level taxonomy for automated vehicles was used to classify smart driving technologies and infrastructure needs. The project used surveys to analyze and gain an understanding of the U.S. general public's perception towards such technologies and their willingness to adopt such technologies. Respondents were asked several anticipatory questions including their technology preferences (buying/selling their vehicles or simply adding new technologies to their current vehicles), and their comfort with and willingness to pay for connected and autonomous vehicles (CAVs). The team found that advanced automation technologies are not yet popular.

This research report also describes the potential crash, congestion, and other impacts of CAVs in Texas, and provides initial monetary estimates of those impacts, at various levels of market penetration. Our findings indicate that CAVs will lead to increased vehicle miles traveled (VMT) because, essentially, drivers experience falling travel time burdens. Their values of travel time that make using a vehicle "costly" tend to decrease because they are more comfortable heading to more distant locations and those unable to drive themselves, such as the handicapped, can now safely travel.

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# Related TxDOT Projects

This report benefits from work conducted in TxDOT Projects 0-6838 and 0-6849, which examine the benefits of a connected and autonomous transport system in Texas and go deeply into the safety, design and operation of the Texas highway system. For details and associated project publications for those and other TxDOT research initiatives, please see the CTR-hosted TxDOT library catalog at http://ctr.utexas.edu/library/.

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# List of Abbreviations and Acronyms

| | |
|---|---|
| AV: | automated/autonomous vehicle |
| CAV: | connected and autonomous vehicle |
| CV: | connected vehicle |
| DARPA: | Defense Advanced Research Projects Agency |
| DSRC: | dedicated short-range communication |
| FHWA: | Federal Highway Administration |
| ITS JPO: | USDOT Intelligent Transportation Systems Joint Program Office |
| ITS: | intelligent transportation systems |
| L0: | Level 0 Automation (No Automation) |
| L1: | Level 1 Automation (Function Specific Automation) |
| L2: | Level 2 Automation (Combined Functions Automation) |
| L3: | Level 3 Automation (Limited Self-Driving Automation) |
| L4: | Level 4 Automation (Full Self-Driving Automation) |
| Lidar: | Light imaging detection and radar, to measure distance via lasers |
| NHTSA: | National Highway Traffic Safety Administration |
| USDOT: | United States Department of Transportation |
| V2I: | vehicle to infrastructure |
| V2P: | vehicle to personal device |
| V2V: | vehicle to vehicle |

# Chapter 1. Executive Summary

"Smart driving technologies" are components that create a more intelligent automotive system, and these technologies can be beneficial in the future for our infrastructure. To analyze these technologies, we anticipated benefits relating to transportation safety, mobility and environment. This involves crash benefits, travel time and congestion benefits, and several cost benefits, amongst others. Aligned with this vision and as part of the TxDOT Project 0-6847 "An Assessment of Autonomous Vehicles: Traffic Impacts and Infrastructure Needs", the objective of this report is to provide a systematic synthesis of contemporary smart driving technologies, including their technological maturity and their potential impacts.

The project began by understanding the current state-of-practice and trends. NHTSA provides a four-level taxonomy for automated vehicles, which was used to classify smart driving technologies and infrastructure needs. Level 0 and Level 1 technology, such as blind spot monitoring and electric stability control, are already entering mainstream adoption. Level 2 technology is promising for the future featuring technologies such as adaptive cruise control (ACC) in conjunction with lane centering or lane keeping assist (LKA). Level 3 and Level 4 technologies, however, have yet to be adopted in the mainstream and pose several large barriers to adoption due to uncertainty in performance and real-world driving. Each of these levels faces many barriers, but the main barriers for such technologies are cost, reliability, and legislation. A large issue with all levels involves cost. However, cost tends to decrease over time and much like cost, we expect that market penetration of these technologies will increase rapidly. Another major barrier involved in this technology's adoption involves licensing and testing standards within the U.S., which are currently being developed at the state level, delaying large-scale adoption. Some technology will also require more information from roadways and needs supporting infrastructural components to function properly such as lane markings and signs. Regarding this need, TxDOT has a key role to play in facilitating the arrival of a substantial presence, which will have many economic and quality-of-life impacts.

The project used surveys to analyze and gain an understanding of the U.S. general public's perception towards such technologies and their willingness to adopt such technologies. The team designed and disseminated a Texas-wide survey for 1,364 completed responses and used those data in the proposed fleet evolution framework to simulate Texans' long-term (2015 to 2045) adoption of connected and autonomous vehicle (CAV) technologies under different technology pricing scenarios (1%, 5%, and 10% annual price-reduction rates). Within the surveys, respondents were asked several anticipatory questions including their vehicle history as well as their future vehicle plans, their technology preferences (buying/selling their vehicles or simply adding new technologies to their current vehicles), and their comfort and willingness to pay (WTP) towards connected and autonomous vehicles. The team found that advanced automation technologies are not yet popular. More than half of the respondents are not willing to pay anything to add the advanced automation technologies such as self-parking valet, limited self-driving [Level 3], and full-self driving [Level 4]. We also found that among single-function (Level 1) and combined-function (Level 2) automation technologies, traffic sign recognition is the least appealing (52.5% of respondents reported $0 WTP), currently least adopted (2%), and anticipated to have the least future adoption (in 2045) by Texans. Blind-spot monitoring and emergency automated braking are the two most appealing technologies for Texans, with the highest adoption rate (59.4%) among Level 1 and Level 2 technologies in 2045 at a 10% annual price-reduction rate. The future adoption rate of connectivity (for DSRC-based basic safety messaging) is estimated to be 57.9% under 10% yearly price reduction scenario. However, it was also found that self-driving valet services and full self-driving (Level 4) technology is estimated to reach adoption rates of just 34.8% and 38.5% respectively and limited self-driving (Level 3) is estimated to be the least popular at a 16.9% adoption rate. Although, Level 3 autonomy may be largely “skipped” by manufacturers (due to difficulties in quickly getting drivers sufficiently context-aware to take over control in situations where the AV technology needs human assistance). Finally, average WTP (of the respondents with a non- zero WTP) to add connectivity, and Level 3 and Level 4 upgrades to their vehicles (new or existing) are $110, $5,551, and $14,589, respectively. Overall, without people’s WTP rising (thanks to good experiences by peers owning such technologies), policies that promote (and/or require such technologies), or unusually fast reductions in technology costs, it is unlikely that technology will be anywhere near homogeneous by 2045.

This research report also describes the potential crash, congestion and other impacts of CAVs in Texas, and provides initial monetary estimates of those impacts, at various levels of market penetration. In this report, it is anticipated that CAVs will lead to increased vehicle miles traveled (VMT) because, essentially, drivers experience falling travel time burdens. Their values of travel time that make using a vehicle “costly” tend to decrease because they are more comfortable heading to more distant locations (may consider replacing air travel with highway travel) and those unable to drive themselves such as the handicapped can now safely travel. Even trucking can become more competitive compared to rail transport through train due to removing driver costs from the scenario. Shared autonomous vehicles (SAVs) may also emerge as a new transportation mode, meaning that some AVs act as driverless taxis or shuttles. In accordance to safety concerns of the driving world, CAVs will likely be safer than human drivers, since human errors are a factor in over 90 percent of U.S. crashes. Results from this project suggest that more than 2,400 lives could be saved each year on Texas roadways by the time 90% market penetration is reached, with over $14 billion in economic savings, or more than $62 billion in comprehensive crash costs (a 75% total reduction in comprehensive crash costs). In terms of cost savings per driver that shifts to CAV operation, around $1,357 per year in added productivity and leisure time can be gained. When comparing these potential impacts over the life of a CAV against the anticipated costs of communication and automation, the net benefits of CAVs appear quite strong. At the 10% market penetration level, privately owned and operated CAVs could have a net present value (NPV) of nearly $13,960 per vehicle, increasing to an estimated value of $27,000 with 90% market penetration.

This research report also describes the potential crash, congestion and other impacts of CAVs in Texas, and provides initial monetary estimates of those impacts, at various levels of market penetration. In this report, it is anticipated that CAVs will lead to increased vehicle miles traveled (VMT) because, essentially, drivers experience falling travel time burdens. Their values of travel time that make using a vehicle “costly” tend to decrease because they are more comfortable heading to more distant locations (may consider replacing air travel with highway travel) and those unable to drive themselves such as the handicapped can now safely travel. Repositioning trips entail AVs dropping off passengers at their destinations and then returning to their owner’s residence (or another location) for free parking, thereby reducing the cost of driving, relative to transit and other alternatives. To anticipate how these behaviors will combine to affect traffic, we created a four-step model using a generalized-cost function of travel time, monetary costs (like parking charges and tolls), and fuel costs. The fact that travel costs impact trip-making decisions, mode choices, and route choices is well-known and fundamental to most travel demand modeling efforts. Three mode choices of driving and parking (using an AV or HV), traveling in a repositioning AV, and transit are considered in the four-step model, with AVs possibly affecting all three choices. The four-step model for determining the impact of AVs allowed for some variation in trip generation, trip distribution, mode choice, and traffic assignment. Trip generation involves estimating trip productions and attractions for each zone. Trip distribution involves splitting a known volume of person-trips and assigning each to a destination. Mode choice determines whether vehicles are assigned to be parking, repositioning, or in transit mode. The second part of our team's travel demand modeling work examines the use of SAVs with dynamic traffic assignment (DTA) (rather than standard, static). DTA allows for generally more realistic with demand changing with time and congestion-feedback models. Along with DTA, to reflect the introduction of AVs on roads shared with HVs, new flow models were developed including a cell transmission model (CTM). The model assumes that all vehicles in the same cell travel at the same speed, class-specific density is uniformly distributed within cells, and backwards wave speed is less than or equal to free-flow speed. The multi-class CTM is shown to be consistent with the hydrodynamic theory. A CTM modeled link flows in our DTA simulations. In these DTA simulations we used a multi-class CTM that admits variations in capacity and backwards wave speed in response to class proportions within each cell (or "sub-link" of the network). The simulation-based dynamic traffic assignment (SBDTA) model involves three main components: a traffic simulator, path generator, and assignment module. As this DTA using a multi-class CTM is more accurate and comparative to realistic traffic conditions than static traffic assignment (STA), it is quite robust. To reduce computational effort and make modeling intersections more tractable, a conflict region model was used in which we discretized the intersections into conflict regions with associated capacity. The conflict region model developed under this work allows for arbitrary policies for vehicle ordering into the intersection. For example, when testing other intersection control such as first-come-first-serve (FCFS) policy (discussed later in this report), the conflict region model was integral in modeling a tractable FCFS policy.

Finally, as presented in this report, the team used the previously mentioned flow and travel demand link-based mesoscopic (mid-scale) models to simulate and model CAVs and to find their effects on congestion and travel times. This allowed the team to analyze the effects of CAVs compared to a control specimen of human driven vehicles (HVs). Within analyzing the effects of CAVs on congestion, a FCFS policy applied to a tile-based reservation (TBR) system was simulated to explore the possibilities of traditional signal substitutes once AV market penetration potentially reaches 100%. The research team also analyzed the effects of rising CAV ownership on transit ridership, CAV repositioning trips, and total personal-vehicle demand using static traffic assignment (STA) simulations. Finally, the team analyzed how shared (and connected) autonomous vehicles (SAVs) may perform relative to privately held CAVs, and how preemptive vehicle relocation and dynamic ride-sharing options affect performance of the downtown transportation network simulated here, over a 2-hour morning-peak period, where most of the trip-making is inbound.

For monitoring CAVs' effects on traffic congestion and travel times, we simulated two smaller arterial road networks, three larger freeway networks, and one large downtown network which were all ranked as part of the top 100 most congested locations and corridors within the state of Texas, so that the results would be widely applicable (TxDOT, 2015). As previously mentioned, the mesoscopic simulation used DTA with a multi-class CTM and a conflict region model to obtain metrics of total system travel time (TSTT) and time traveled per vehicle. Experiments consisted of simulating varying demands and varying proportions of AVs to HVs with traditional signals, and then running simulations using 100% AVs with a FCFS tile-based reservation (TBR) system and varying demands.

Within our simulator, differences between AVs and HVs were highlighted by assuming and applying a reaction time of 1 second for HVs and 0.5 seconds for AVs. As reaction time decreases, both the capacity and backwards wave speed increase. The car-following model predicts a triangular fundamental diagram, between flow (on the y-axis) and traffic density (on the x-axis). Vehicle speed is bounded by the free-flow speed in the uncongested regime. In the congested region, speed is limited by vehicle density.

After running many simulations on different networks with different demands and AV proportions, the team observed that increasing the proportion of CAVs always reduced vehicle travel time if one assumes that CAVs' faster reaction times (vs. HVs) reduces their car-following headways, thus increasing lane capacities and signal-phase capacities naturally. While reduced headways are a reasonable expectation for advanced stages of CAV adoption, in the early stages, due to either cultural norms or caution on behalf of manufactures, there may be no reduction in headway due to CAVs.

The team also found that the FCFS reservations performed worse than traditional signals for some networks, especially in freeway networks and closely packed arterial networks. At high levels of demand, reservations do not allocate capacity as efficiently as signals or provide progression across upstream and downstream signals, resulting in queue spillback along arterials. Although some exceptions to the FCFS TBR system improving traffic congestion and decreasing travel times presented themselves during simulations, FCFS did especially well on the large scale downtown Austin network, resulting in a nearly 78% reduction in travel time across the network (with 100% AVs with reduced reaction times). The reason for such a drastic decrease in travel times using TBR compared to some arterial network exceptions is that congested intersections might be avoided by dynamic user equilibrium route choice decisions. The team also used STA simulations to observe the effects of having more classes of CAV users with different values of travel time (VOTTs) and to see if there is any change in demand for these trips. It was observed that, as more travelers gain access to CAVs, the travel time (or "cost") per trip generally falls. It was also observed that transit demand and parking demand both fall as more travelers can avoid parking costs through repositioning in SAVs and CAVs, also allowing for the reallocation of downtown parking space.

This research report analyzes the potential benefits and impacts of smart driving technologies consisting of CAVs and SAVs within our current transportation networks relating to transport safety, mobility and environment. The report also shows the methodology behind models and simulations used to represent and predict such technologies.

# Chapter 2. Introduction

"Smart driving technologies" refer to telematics, sensing, and automation-based technologies and technology packages equipped on autonomous vehicles (AVs) and connected vehicles (CVs). These represent potentially disruptive yet beneficial changes to our transportation system and the society. They have tremendous potential to improve vehicle safety, congestion, travel costs, and freight movement, while impacting a variety of related driver behaviors and travel choices**.** In recent years CV and AV technologies have undergone dramatic advances. Auto manufacturers, parts suppliers, and technology firms are developing cars and trucks with the ability to communicate with one another and with infrastructure, while also finding ways to increasingly transfer driving responsibilities from human drivers to the cars themselves. These new technologies will undoubtedly have profound impacts on our current and future transportation systems, providing more transportation options and possible benefits than we are aware of today. It is evident that such changes will profoundly change the landscape of traffic operations, infrastructure design and maintenance, among others, in Texas and elsewhere. Our evolving transportation systems should harness the power of smart driving technologies to address emerging challenges.

As with any new technology, prior to implementation CAV/AV technology must be understood, and its effects carefully predicted, to correctly plan for the transition. Cost/benefit analyses must be conducted and the effects of the new technology must be predicted as accurately as possible. To understand the current state of automated technology within vehicles and transportation, our team conducted research on current and future autonomous technological possibilities. The application of such technology has enormous potential within several different fields of infrastructure, and our team conducted research on how CVs and AVs operate.

CVs are cars and trucks that rely on communication technologies to facilitate vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. The USDOT defines the CV technology platform as a multimodal initiative that aims to enable safe, interoperable, networked wireless communications among vehicles, the infrastructure, and passengers' personal communications devices (USDOT 2015). Some of the potential CV applications in testing and development include cooperative adaptive cruise control (CACC), incident warning, traffic signal priority, emergency vehicle and/or transit priority, and smartphone-enabled pedestrian safety applications. Citing the tremendous potential gains for safety, mobility, and the environment enabled through these and other applications, the National Highway Traffic Safety Administration (NHTSA) recently announced that it would consider mandating V2V communication facilitated through dedicated short-range communication (DSRC, i.e., wireless radio communication), at some time yet to be determined (NHTSA, 2014). With several areas such as Wyoming, Ann Arbor, Michigan, New York City, and Tampa, Florida implementing and testing next-generation CV technologies including V2I technology within roadside units and upgraded signal systems, data is being collected and eventually distributed to road users. CV market penetration is likely to grow quickly with numerous vehicles manufacturers such as BMW, Volkswagen, Mercedes-Benz, Ford, GM, Toyota, and many others dedicating significant efforts toward developing CV technologies and successfully implementing them into their vehicles.

Autonomous vehicles (AVs), although a more recent concept for the transportation world (compared to CVs), still possesses an already long and growing list of entities involved in the technology. Google's self-driving cars have been driven over 1.2 million miles since the project started in 2009 (Google, 2015). As of May 2015, their self-driving vehicle fleet had been involved in just 12 minor collisions (all of which involved a human driver deemed at fault, rather than Google's AV technology). Currently, the list of entities involved in the autonomous vehicle world include auto manufacturers such as Audi, BMW, Ford, GM, Mercedes-Benz, Nissan, Toyota, Volkswagen, and Volvo along with their non-traditional counterparts at Tesla and Local Motors, and even technology companies such as Apple and Google. An AV may have full self-driving capabilities, or it may simply be equipped with a lane keeping assist, where the steering gently nudges the vehicle back toward the center of a lane if the driver appears to be drifting. NHTSA identifies five levels of AV technology as follows (NHTSA, 2013), with Levels 1 and Level 2 technology already commercially available:

- *No-Automation (Level 0):* The driver is in complete and sole control of the primary vehicle controls—brake, steering, throttle, and motive power—at all times.
- *Function-specific Automation (Level 1):* Automation at this level involves one or more specific control functions. Examples include electronic stability control or pre-charged brakes, where the vehicle automatically assists with braking to enable the driver to regain control of the vehicle or stop faster than possible by acting alone.
- *Combined Function Automation (Level 2):* This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering.
- *Limited Self-Driving Automation (Level 3):* Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time. The Google car is an example of limited self-driving automation.
- *Full Self-Driving Automation (Level 4):* The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Such a design anticipates that the driver will provide destination or navigation input, but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles.

Researchers have generated a vast array of ways to implement and integrate CAVs and AVs with one common conclusion: CAVs and AVs have the potential to reduce travel times and make current transportation systems more efficient. Other technologies such as shared autonomous vehicles (SAVs) with dynamic ride-sharing as well as repositioning trips and first-come-first-serve (FCFS) reservation intersections are also analyzed in this report. The transition from HVs to AVs will be long, with many barriers along the way including some of the largest challenges: Cost, reliability, and legislation. As these barriers are overcome, we expect to see rapid increases in market penetration of CAV and AV technologies. One of the largest challenges we face as we attempt to smoothly transition to a fully autonomous world, is successfully pushing the technology into mainstream-adoption. Legislation will add liabilities to many aspects of AVs, and is currently handled by state governments in the U.S., which may lead to a decentralized establishment of certain technologies. CAVs are currently too expensive for most consumers to afford currently, posing a large cost issue. There are also cyber-security related concerns with implementation of such a large and connected network. Gaining a large-scale adoption of a technology is integral in establishing its implementation, so to understand the public's thoughts and views on such technologies, our research team designed and disseminated a Texas-wide survey for 1,364 completed responses. We collected data such as willingness-to-pay (WTP) and comfort with new technologies, then used the data in proposed fleet evolution framework to simulate Texans' long-term (2015-2045) adoption of CAV technologies under different technology pricing scenarios ranging from 1%, to 5%, to 10% annual price-reduction rates. The results confirm that the transition to Level 3 and Level 4 technologies will take time, but long-term trends are certainly moving in that direction.

To help delineate how smart driving technologies will achieve system benefits, a comprehensive understanding of the transportation system impacts of these technologies is crucial. Emerging smart driving technologies along with innovative traffic system management and operation strategies provide chances for TxDOT to achieve stated key transportation goals: maintaining a safer system, addressing congestion, and connecting Texas communities. To showcase these possible benefits, accurate results must be produced to support these assertions. With traffic modeling being quite capable of creating simulations parallel to the real world with time varying components such as in dynamic traffic assignment (DTA) and with the use of models such as the cell-transmission model (CTM), researchers can now produce results that will be effective in convincing the public of smart driving technologies' ability to reduce congestion and travel times between locations. This report is concerned with the interplay between HVs and CAVs, as during the transition period between the two, there will be a proportion or mix or both technologies on the road. This report outlines the test networks and results used to see how travel times are affected by the inclusion of CAVs and SAVs at different roadway penetrations. In order adequately explore travel-time effects, multiple types of roadway networks are tested. These networks are also tested under different, limited-period scenarios, like rush-hour conditions vs. lower-demand settings. Once the decision of which networks to use and what scenarios to model were decided upon, simulations must be performed to demonstrate the effects of CAVs at different penetrations. These results can help city planners prepare for when modeling future networks, bearing in mind projected increases in CAV availability and use.

The objective of this research report is to provide a systematic synthesis of contemporary smart driving technologies, including their technological maturity and their potential impacts. This report is a complete showcase and analysis of findings within research conducted under TxDOT research project 0-6847: "An Assessment of Autonomous Vehicles: Traffic Impacts and Infrastructure Needs.

## 2.1 Synthesis of Smart Driving Technologies

### 2.1.1 Overview: NHTSA's Taxonomy

The advances of robotics, navigation, sensing, computer vision and high performance computing in the last two decades have stimulated new automotive technologies, mainly along two streams: (1) vehicle automation, which consists of technologies concerning automation of vehicle control functions (such as steering, throttle and braking) without direct driver inputs; and (2) vehicle connectivity, which consists of different vehicular communication technologies (i.e., connected vehicles), such as V2V (vehicle to vehicle), V2I (vehicle to infrastructure) and V2P (vehicle to personal device). The emergence of new automotive technologies will change motor vehicles and the relationships of drivers with them, over the next several decades. Vehicle control systems can also smooth traffic flow, through automatic control of acceleration and brakes, which as the ability to reduce headways and increase throughput rates of current roadways. In addition, the driving experience and fuel consumption can be simultaneously improved. The new technologies may also eliminate a large number of crashes, through effective crash avoidance systems. When vehicular automation and connectivity are synergized, new traffic signal control systems will become possible which are anticipated to reduce intersection and freeway delay significantly.

Recognizing the prominent safety, environment and mobility potential of emerging automotive technologies, NHTSA (2013) released a Preliminary Statement of Policy Concerning Automated Vehicles. In this statement, NHTSA provides definitions of different levels of automation, current automated research programs at NHTSA, and principles recommended to States for driverless vehicle operations (including, but not limited to, testing and licensing). According to NHTSA's definitions, the term 'automated vehicles' specifically refers to "those at which at least some aspects of a safety-critical control function (e.g., steering, throttle, or braking) occur without direct driver input". Vehicles that can provide safety warnings but without these mechanized control functions are not automated. For the purposes of this report, we adopt NHTSA's definition (see Table 2.1). As a side note, besides the definitions of NHTSA, SAE International released another set of definitions (SAE, 2014), categorizing automation into six levels. These definitions are similar to NHSTA's in that both capture the decreasing level of engagement of human drivers in dynamic driving tasks, including the operational and tactical aspects.

**Table 2.1: NHTSA's Definitions of Vehicle Automation**

Source: (NHTSA, 2013)

| **Four Levels of Automation Defined by NHTSA** |
|---|
| **No Automation (Level 0):** Vehicles have certain driver support/convenience systems but do not have control authorities over steering, braking or throttle. Driver is in complete and sole control of the primary vehicle controls at all times, and is solely responsible for monitoring roadway conditions. |
| **Function-specific Automation (Level 1):** Automation at this level involves one or more specific control functions. Examples include electronic stability control or pre-charged brakes, where the vehicle automatically assists with braking to enable the driver to regain control of the vehicle or stop faster than possible by acting alone. |
| **Combined Function Automation (Level 2):** This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering. |
| **Limited Self-Driving Automation (Level 3):** Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time. The Google car is an example of limited self-driving automation. |
| **Full Self-Driving Automation (Level 4):** The vehicle is designed to perform all safety- critical driving functions and monitor roadway conditions for an entire trip. Such a design anticipates that the driver will provide destination or navigation input, but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles. |

According to these definitions, with increasing levels of automations, drivers have decreasing engagement in traffic and roadway monitoring and vehicle control. From level 0 to level 4, the allocation of vehicle control function between the driver and the vehicle ranges from full driver control, driver control assisted/augmented by systems, shared authority with a short transition time, shared authority with a sufficient transition time, to full automated control. A detailed comparison along with examples is presented in Table 2.2.

**Table 2.2: Comparison of Different Automation Levels**

Source: (NHTSA, 2013)

| | Vehicle Controls* | Traffic and Environment (Roadway) Monitoring | Examples |
|---|---|---|---|
| **L0** | Drivers are ***solely responsible*** for all vehicle controls. | Drivers are solely responsible; System may provide driver support/convenience features through ***warning***. | Forward collision warning (FCW); lane departure warning; blind spot monitoring; automated wipers, headlights, turn signals, and hazard lights, etc. |
| **L1** | Drivers have overall control. Systems can ***assist or augment*** the driver in operating one of the primary vehicle controls. | Drivers are solely responsible for monitoring the roadway and safe operation. | Adaptive cruise control; automatic braking (dynamic brake support and crash imminent braking); lane keeping; electric stability control (ESC). |
| **L2** | Drivers have ***shared authority*** with system. Drivers can cede active primary control in certain situations and are physically disengaged from operating the vehicles. | Drivers are responsible for monitoring the roadway and safe operations and are expected to be ***available*** for control ***at all times*** and ***on short notice.*** | Adaptive cruise control combined with lane centering. |
| **L3** | Drivers are able to ***cede full control*** of all safety-critical functions ***under certain conditions***. Drivers are expected to be available for occasional control, but with ***sufficient transition time.*** | When ceding control, drivers can ***rely heavily on the system*** to monitor traffic and environment conditions requiring transition back to driver control. | Automated or self-driving car approaching a construction zone and alert the driver in advance. |
| **L4** | Vehicles perform ***all safety-critical driving functions*** and monitor roadway conditions for an entire trip. ***Drivers*** will provide destination or navigation input, but are ***not expected to be available for control*** at any time during the trip. | System will perform all the monitoring. | Driverless car. |
| L0 to L4= Level 0 to Level 4 automation;<br>Vehicle controls refer to braking, steering, throttle control, and motive power. | | | |

Research and development on connected vehicles have drawn significant attention in recent years. Dedicated short-range communication (DSRC) and cellular technologies are two major technologies in a connected-vehicle system and its applications. The low latency feature makes DSRC suitable for safety-sensitive applications, such as forward collision warning. Because such applications require a certain level of market penetration to take effect, it is anticipated that governmental regulations are needed at the initial stage of technology deployment. In 2014, NHTSA released a notice of making a proposal to mandate DSRC on light vehicles in 2016. In comparison, car manufactures and technology companies are engaged in creating/implementing cellular-based communications and their applications in emergency response (e.g., the OnStar system of General Motors) and infotainment (e.g., the CarPlay system of Apple).

Level 1 and 2 automated vehicles are readily available on the market, with self-parking, adaptive cruise control, lane departure warning, and collision warning systems in place. In particular, among various level 1 automated technologies, electronic stability control (ESC) is mandated by NHTSA on all new light vehicles since manufacture year 2011. It was also proposed by NHTSA in 2011 that ECS be mandated on heavy vehicles. Along with ESC, lane departure warning (LDW) and forward collision warning (FCW) are two other crash avoidance technologies NHTSA has been looking into and encourages consumers to consider. Besides crash avoidance technologies, NHTSA is also engaged in automatic braking technologies, which include dynamic brake support and crash imminent braking, all of which fall into the category of Level 1 automation.

While the level 0, level 1 and level 2 technologies are ready for large-scale deployment or purchase, the technology costs of level 3 and level 4 automation are currently high and likely to remain high for another decade or so. Besides the cost, there exist other major barriers in legislation and regulation, public acceptance, security and reliability of technologies.

### 2.1.2 Level 0 Technologies

*Forward Collision Warning*

NHTSA defines a forward collision warning (FCW) system as “one intended to passively assist the driver in avoiding or mitigating a rear-end collision via presentation of audible, visual, and/or haptic alerts, or any combination thereof.” An FCW system has forward-looking vehicle detection capability, using sensing technologies such as camera, radar and Lidar. Sensor data will be processed and analyzed, and alerts will be provided if a collision with another vehicle is imminent.

*Blind Spot Monitoring*

There are two different types of blind spot monitors—active and passive. An active blind spot monitor generally uses a radar or a camera to detect when another vehicle is in the blind spot of the vehicle in question. If any such vehicles are detected, the vehicle in question will notify its driver. The type of notification will generally depend on how likely it is that two vehicles will collide; as the likelihood of collision increases, so does the magnitude of the warning that one receives. The warning may be as minute as a flashing light in the driver’s peripheral vision or as large as a seat vibration; the most advanced systems even have the capability to steer the car back into safety if collision would be otherwise imminent. It is also important to note that these features can be turned off since there have been people who have expressed frustration with these warnings being activated too often in heavy traffic.

In 2005, Volvo was the first manufacturer to introduce blind spot technology under the name Blind Spot Information System (BLIS). Originally BLIS used cameras but the newest BLIS technologies use radars instead. Ford uses a similar system to Volvo, and many other manufacturers currently have very similar blind spot technologies, as well, such as Audi's Audi Side Assist. Infiniti's blind spot system is more advanced, which consists of two sub-systems: the Blind Spot Warning (BSW) and the Blind Spot Intervention (BSI) systems. The former notifies the driver of blind spot vehicles, while the latter will work to keep the vehicle in its lane if it is not safe to change lanes (Lampton, 2012). It is important to note that the performance of these blind spot technologies decreases under certain situations, such as inclement weather (Travers, 2008).

### *Lane Departure Warning*

Lane departure warning (LDW) is similar to blind spot monitoring, in that its main goal is to prevent the vehicle from unsafely exiting its lane. LDW uses a camera to detect lane markings and will alert the driver if the vehicle begins to leave its lane, but only if the turn signal is not activated. The system will emit an audible or visual alert, and advanced applications are able to take active control of the steering wheel to correct the vehicle's heading automatically (Level 1). It is anticipated that in the future, these systems will incorporate features such as monitoring driver's eye activities to determine drowsiness (Carmax, 2015). Lane departure warning is available on some Infiniti models as an option, with the package ranging from $3,600 to $10,500 as of December 2016.

### *Traffic Sign Recognition*

Traffic sign recognition (TSR) is used to identify and display upcoming traffic signs that are often missed by drivers. The system functions using a camera to detect oncoming traffic signs and a traffic sign recognition system that identifies the signs recorded by the camera, which is displayed to the driver. Depending on the system used, road sign information is displayed on either the vehicle's instrument panel cluster or the driver's navigation system.

Cameras placed behind the vehicle's rear view mirror record oncoming traffic signs and transmit the information to the vehicle's traffic sign recognition system. Since road and traffic signs are manufactured according to strict standards, traffic signs can be identified by shape and color. In a natural environment, there are three main challenges that object recognition software encounter: poor lighting and visibility, the presence of other objects, and the variation of traffic and road signs (systems may be designed specific to a region to address this concern). Various difficulties arise under poor weather and night-time conditions that influence camera detection of color, hue, and saturation (Fleyeh & Dougherty, 2005). Under these conditions vehicle sensors will notify the driver of these restrictions.

Nevertheless, TSR systems have been developed with high detection accuracy and may be additionally supplemented by information from digital maps and navigation systems. (Mobileye, 2015). The system can also be used to help enforce the legal speed limit and to warn drivers of other warning signs on the road. If the driver exceeds the posted speed limit, the displayed speed limit sign will flash, and the system will make warning noises to warn the driver. These additional warning functions are specific to the TSR software and may be turned off if desired.

The TSR systems' range and ability to operate at a high performance at high speeds is reliant on the camera's image resolution. Future developments aim to broaden the range of detectable signs.

*Left Turn Assist*

Left turn assist (LTA) systems use a camera and GPS to warn drivers attempting a left turn when it is unsafe to enter the intersection. The camera functions by registering lane markings and lane boarders on the road, while the vehicle's position and location is determined using the navigation system.

When LTA is activated, three laser scanners, installed on the front end of the car, begin sensing for approaching cars, trucks, and even motorcycles up to 100 meters (330 ft.) away. If the sensors detect an approaching vehicle from the opposite direction and the driver's vehicle continues to move into the intersection, the LTA system will generate both warning sounds and signals on the vehicle and activate the vehicle's automatic breaking. Without an automatic braking response, the vehicle would continue to move into the intersection, resulting in a possible collision (BMW Group, 2011). The automatic braking response is deactivated when the driver applies pressure to the vehicle's brakes, and the LTA can also be overridden. Note that LTA is only designed to work at very low speeds at less than 10km/hour (roughly 6mph).

LTA was first publicized by BMW in 2011 and further research is currently being conducted on vehicle-to-vehicle (V2V) communication for better implementation of this feature. (NHTSA, 2014) V2V communication increases safety by using a wireless local area network to detect other vehicles with similar concealed devices. The technology is proposed to significantly decrease the number of crashes at intersections and can be used to warn drivers of the conditions at approaching intersections.

*Automatic Collision Notification*

The goal of automatic collision notification (ACN) systems is to provide more rapid and informed emergency medical responses in the event of a collision. An effective ACN system is able to notify authorities with information such as the location, severity of an existing collision, probability of serious injury, and provide a voice link between the emergency response personnel and the vehicle's occupant/s. This is a safety-oriented, in-vehicle emergency response feature that can greatly reduce the reaction time of emergency vehicles in the event of a collision. Furthermore, if authorities are properly notified of the collision severity and nature, preparation to treat injured occupants can be efficiently enhanced.

ACN systems are not a newly discovered technology as they have existed since the late 1990s (Wu, Subramanian, Craig, Starnes, & Longthorne, 2013). However, this technology has rapidly progressed over the years providing more accurate and detailed information of collisions involving vehicles equipped with ACN systems. More advanced ACN systems have been called AACN systems. OnStar is one of the most well-known AACN systems, but BMW Assist, Toyota Safety Connect, Ford's 911 Assist, and others perform many of the same basic functions. Utilizing a Global Positioning System (GPS) receiver to locate the vehicle, an accelerometer to detect the collision, many sensors to determine the severity of the collision, and a cellular network to communicate with the vehicle occupants, AACN systems prove to be more effective in providing earlier collision notification than relying on the general public to report a collision.

Wu, Subramanian, Craig, Starnes, & Longthorne (2013) conducted a study based on 4 years of data retrieved from the Fatality Analysis Reporting System (FARS) to compare the effects of earlier versus later emergency medical service, or EMS, notification on the survival rate of vehicle occupants involved in collision. With a total of 41,862 cases, results showed that fatality hazard for the less favorable group (later notification) was 2.4% higher than the favorable group (earlier notification). Furthermore, the results showed that 1.84% of the group with later EMS notification group could have been saved with an earlier notification of collision to EMS by application of an ACN system.

### *Adaptive Headlight*

Many manufacturers currently have adaptive headlights technology. Though there is not any one specific way that this technology functions or is integrated with the vehicle, there are themes that are common to all manufacturers. For example, the BMW adaptive headlights have cameras that detect the traffic situation, even in the far distance, and pass this information on to the headlights. Then, the headlights adapt the light distribution accordingly so that no oncoming traffic or preceding traffic will be affected by the light coming from the user's vehicle. For example, one set of lights may be low beam and another may be high beam, or the lights may be swivel if a curve is detected ahead. This is a feature that can drastically improve safety because the driver will be able to detect dangerous situations earlier since more lighting will be available in the direction of travel. The idea, according to BMW, is to give the driver more notice about an object he or she might cross paths with before normal headlights will reach that object (BMW, 2012). Studies have shown the danger of road accidents at night is reduced with this technology.

In order for Texas and the United States to be able to leverage this technology to increase safety as much as possible, the current federal regulations on headlight standards would need to be revised. If this happens, the Highway Loss Data Institute estimates that by the year 2044 95% of the registered vehicle fleet will have adaptive headlights; if additional mandates are introduced to encourage adaptive headlights, the expected date could be as soon as 2039.

### *Driver Monitoring*

Driver monitoring systems (DMS) are safety applications used to track the driver's inattention, (e.g., distraction, fatigue) while operating a vehicle. Driver inattention can be described as having a lack of required, critical attention that results in unsafe driving. An estimated 25% of police-reported crashes are related to driver inattention, according to the National Highway Traffic Safety Administration, and over half of those inattentive crashes (16% of the total) are due specifically to distraction (Ascone, Lindsey, & Varghese, 2009). With the use of a DMS, these distracted and inattentive crashes could be significantly reduced.

DMSs are designed to monitor vehicle characteristics (e.g., speed, position, acceleration, seat belt use, seat occupancy, etc.). The data that is monitored can then be used in several ways. One use of the information obtained by the system is to communicate with and alert the driver and/or drivers in surrounding vehicles of roadway safety concerns, abnormal driving characteristics, and potential impending collisions. Recorded data can also serve as a means of evidence in an investigation from a collision or accident. Driver monitoring systems can also be used to determine cost of insurance/ liability in the event of a crash.

A general monitoring system uses infrared sensors and cameras to record the driver's aptitude. The sensors and cameras are used to track and record any detection of drowsiness or inattention while the vehicle is being operated. Driver monitoring systems require a strict real-time performance capability. One technology used to achieve this is image processing algorithms (e.g., eyelid movement, head position, yawning). If the monitoring system detects driver inattention, it will alert the driver and proceed with an appropriate action. Depending on the type of system installed, feedback can be visual, tactile, or aural.

One obstacle for driver monitoring systems is meeting the need of accurately recording spatially large head turns while driving, in order to receive the most precise data possible. (Tawari, Martin, & Trivedi, 2014) proposed a continuous head movement estimator (CoHMET), a method of facial detection that uses multiple cameras with continuous resolution to provide independent perspectives. The images processed from these cameras are then combined to produce a final estimation of the head pose. CoHMET was tested twice, first with two cameras and then with three. The final results of this study showed that the three-cameral approach showed the most favorable results, with 96.1% reliable head movement tracking. This indicates that such a system could provide a strong degree of certainty for detecting distracted or inattentive drivers.

### 2.1.3 Level 1 Technologies

*Adaptive Cruise Control*

Most ACC systems use a radar or laser (less popular) headway sensor and a digital signal processor to determine the distance and speed of the vehicle ahead (Honda Motor Co. Inc., 2015). Other automobile manufactures prefer an optical system using stereoscopic cameras, such as Subaru. (Howard, 2013) ACC systems rely on two sensors that use infrared detection: the sweep long-range sensor and the cut-in sensor. The sensors emit beams of infrared light, which are reflected by the vehicle ahead and are captured by a receiver. The sweep long-range sensor is only able to detect vehicles directly ahead and uses a narrow infrared beam. To deal with curved roads, the system uses a solid-state gyro that determines the curve-radius, notifying the sweep sensor to turn accordingly. The cut-in sensor deals with cars that suddenly merge into the lane. This sensor has two wide beams that detect vehicles in adjacent lanes that are moving at least thirty percent as fast as the moving vehicle. The cut-in sensor does not detect stationary objects along the side of the roadway. All of the sensor information is transmitted to a central controller, called the Vehicle Application Controller, which reads the desired settings of the driver. The central controller also controls the engine and/or braking system to respond appropriately.

*Automatic Emergency Braking*

Also known as forward collision avoidance technology, automatic emergency braking (AEB) has the potential to significantly decrease the number and severity of collisions, by automatically applying the brakes to the vehicle when an imminent collision is predicted. AEB systems are made up of sensors that observe and categorize objects within range, control systems to depict the data produced by the sensors, and automatic braking actuation system to physically stop or slow the vehicle. Many vehicle manufactures, including General Motors, Chrysler and Toyota have already begun incorporating AEB systems in their newer luxury model vehicles.

These results strongly indicate that by application of a Baseline AEB system, the number of visible pedestrian, and rear-end collisions, as well as objects struck straight on crashes would decrease significantly. Results also showed that a reduced impact speed for unavoidable accidents would be accomplished for many other collisions with the application of an AEB system. Since impact speeds are non-linearly related to risk of injuries, reduced collision speeds produced by AEB systems have the potential to substantially reduce injury risk.

*Lane Keeping*

Both lane-centering and lane-keeping technologies are used to keep automobiles from drifting out of a lane on high-speed roads. Lane-keeping was first developed to correct vehicles by braking slightly to warn the driver. Now with lane-centering, the system uses electronically controlled steering to help maintain a center position in the lane of the vehicle.

The technology uses a camera mounted on a vehicle's windshield to watch the lane markers on the road; the camera is able to recognize both yellow and white lines. If the camera detects that the driver is beginning to drift out of a lane without the use of a turn signal, the device will alert the diver with a warning sound, and then activate the electronic power steering control to steer the vehicle back into the center of the lane (Toyota Motor Corp., 2015). One must note that the electronic steering is a safety device that may be overridden by the driver.

*Electric Stability Control*

Electronic Stability Control (ESC) is potentially one of the most beneficial safety technology introduced to date. It is an extension of the antilock braking technology and the traction control system technology (Sivinksi, 2011). ESC is one of the main active safety systems (meaning it works to prevent accidents rather than working to prevent injuries once an accident occurs). It works to ensure that that a driver can always be in full control of his or her vehicle. ESC helps prevent skidding and rollovers which can often happen during high-speed maneuvers or on slippery roads making it an immensely valuable feature on rainy days (MEA Forensic Engineers & Scientists, 2013).

ESC works by measuring the steering input (i.e., how much the driver has turned the steering wheel in degrees) and then comparing this to the yaw angle (i.e., how much the car has actually turned). If there is any difference in these values, then the ESC will automatically apply brakes on any of the wheel(s) as needed to steers the car in the desired direction. Also, if needed, the engine throttle can be reduced to avoid power skids, (Cars.com, 2012). This technology essentially allows the vehicle to maintain traction with the road as long as possible, which can provide the driver with enough time to regain control, thus preventing skidding and rollovers.

*Parental Control*

In recent years some car manufacturers (e.g., Ford, GM) offered a parental control feature aimed at increasing safety of teenage drivers as an optional add-on. This strategy aims to reduce the risk and severity of crashes by using a series of different technologies that monitor and control teenagers' driving behavior.

For example, the first parental control system introduced by Ford, MyKey (Ford, 2015) includes features such as: speed control that allows the owner to set a limit to 80 mph, volume control that allows the owner to adjust the volume of the radio remotely, a belt reminder system that can mute vehicle's radio and chime for few seconds, an earlier fuel reminder, and a speed reminder at 45, 55 or 65 mph. Chevrolet's Malibu model, on sale toward the end of 2015, will provide the "Teen Driver" system. This tool can "help encourage safe driving habits" (General Motors, 2015) by providing a series of features such as stability control, front and rear park assist, side blind zone assist, rear cross traffic alert, forward collision alert, daytime running lamps, forward collision braking, traffic control, front pedestrian braking.

Given the early life of this tool, at the moment there are no available data or analyses to quantify the benefits of this measure. However, presuming that this feature will be widely developed by other manufacturer competitors (in US), parental control could become within few years an affordable standard option. Hence, it is reasonable to expect considerable benefits from increased safety among teenage drivers. No particular barrier to the implementation and market penetration of this technology is foreseen.

### 2.1.4 Level 2 Technologies

*Traffic Jam Assist*

Traffic jam assist (TJA) functions on limited access highways at slow speeds (Andrew, et al., 2013). TJA provides for the full control of driving in congested conditions. The drivers will still have direct supervision of the vehicle during this process, will receive continuous system feedback, and is responsible for the overall operation of the vehicle. The Mercedes S-Class is representative of TJA. The driver is expected to be engaged in driving with TJA, with hands on the steering wheel. If the system detects that the driver is not touching the steering wheel a warning will be issued and the TJA function will be disabled after a few seconds. The European HAVEit project demonstrated this concept on heavy trucks. In this system, a truck driver in congestion can cede the speed and steering control.

*High Speed Automation*

General Motors described a “super cruise” system, which can provide full-speed range ACC in conjunction with lane keeping. Cameras and radars are used for sensing, and the system can automatically steer, accelerate, and brake in highway driving. Drivers may leave hands off the steering wheel, until the driver wants to change lanes, the system can no longer handle deteriorating road conditions, or other issues occur. Other car manufactures that have developed similar products include Honda (Europe), Nissan, Audi, and BMW. Nissan's system automatically reduces the discrepancies between the intended and actual path, and claims to reduce driver fatigue by reducing fine-grained steering adjustments. BMW’s system not only provides lateral and longitudinal control, but also responds to merging traffic from the right and can perform a lane change when safe. Google has also developed automated vehicles (i.e., Google driverless cars) that can operate up to 75 mph on highways. Google’s car combines ACC and lane keeping, but does not change lanes automatically.

*Automated Assistance in Roadwork and Congestion*

The Automated Assistance in Roadwork and Congestion (ARC) was demonstrated in the HAVEit project of Europe (HAVEit, 2015). This system aims to enable automated driving through a work zone, so as to support the driver in overload situations like driving in narrow lanes of roadwork (i.e., work zone) areas (Strauss, 2010). It considers the possibility that lane lines are not accurate, and it uses other objects, such as trucks, beacons, and guide walls for guidance.

### 2.1.5 Level 3 Technologies

In Level 3, direct supervision of drivers is not needed, and the driver is only needed for control with certain degree of notice, with sufficient transition time.

*On-Highway Platooning*

In a platoon, vehicles can have a shorter headway between each other. This technology looks into the possibility of letting a human drive the lead vehicle and is followed by fully automated following vehicles in platoon. A prototype of this technology was developed in Europe's SARTRE project using Volvo cars and trucks.

*Automated Operation for Military Applications*

The U.S. Army sponsored development of the Autonomous Mobility Applique System, a program designed to retrofit existing military trucks with a range of systems, from active safety to full Level 3 automation. The purpose of this project is to allow military vehicles operate on any road types and off-road.

### 2.1.6 Level 4 Technologies

*Google's Self-Driving Car*

In May of 2014, Google presented a new prototype of driverless car that does not have pedals or steering wheels. In December of 2014, Google released a fully functioning prototype of their driverless car and planned to test it on San Francisco Bay Area roads beginning in 2015. According to the latest update from Google in December 2014 (Google, 2015), a safety driver is still needed to oversee the vehicle, and manual controls are needed in the current testing stage.

Currently, this latest prototype of driverless car has not been tested in heavy rain or snow. Moreover, Google's driverless car primarily relies on pre-programmed route data, and cannot recognize traffic lights. In addition, this prototype is limited in identifying trash and debris on the roadway. The Lidar technology cannot spot potholes or recognize humans signaling the car to stop. Google has noted that it expects to solve these issues by 2020 (Google, 2015).

*Emergency Stopping Assistant*

A dead man's switch, or kill switch, is a safety-oriented feature that is installed to give the "driver" the ability to cease operation of the vehicle in the case of an emergency or driver incapacitation. The dead man's switch has been most commonly used in the train and railway industry in the form of a lever or pedal that must be engaged for the machine to remain active. If disengaged, the machine then would alarm the driver, slow to a stop, and shut down. Conceptually, this type of switch is ideal for a train on tracks, but when it comes to a vehicle on a roadway with other vehicles, it becomes more complicated.

A distinct kill switch was included in a Google self-driving car as a large red button located just below the gearshift. Google's kill switch differs from conventional and most previous kill switches because rather than having to have constant contact with the switch for the machine to remain active, the vehicle remains active until the switch/button is activated. After applying the switch, however, Google's car will automatically withdraw all self-driving capabilities and return to human-driving mode.

*Automated Valet Parking*

With automated valet parking feature, some of vehicles are able to automatically park only after a spot has been located by the driver. Such vehicles are equipped with technology known as Intelligent Parking Assist Systems (IPAS) or Advanced Parking Guidance Systems (APGS). These systems were first developed by Toyota in 2004 and are now available in multiple luxury models. Completely autonomous self-parking valet systems enable a vehicle to be dropped off at the entrance of a parking garage, locate a parking spot, park, and return to driver when summoned without any human interaction. Manufacturers such as Audi, BMW, and Volvo have already developed such systems and are beginning to test them in controlled settings (Wired.com, 2013).

With the deployment of this new and rapidly advancing parking technology, and as the penetration rate for vehicles equipped with this technology, increases. With sufficient market penetration, parking garages may be built more compactly since there may be no need for extra space between such vehicles to allow passenger to get in and out. Lutin et al. (2013) also predicted that parking garages may be relocated further from the buildings they serve. However, as parking infrastructure becomes more compact, it is likely that curb-side loading areas will need to be enlarged to accommodate new congestion due to drop- offs and pick-ups.

The general benefits of auto-valet include saving time and money, increasing safety, and using available parking space more efficiently.

## 2.2 Discussion

### 2.2.1 Driving Forces

*The Public*

AVs have the potential to fundamentally shift the paradigm of driving, by offering an array of safety and driver-assistance features. These features will directly benefit drivers in various ways, and therefore, the public will be interested in purchasing cars with smart driving technologies. First and foremost, automated vehicles can substantially reduce or mitigate crashes. Second, smart driving technologies will free the drivers from driving tasks, and thus reduce their stress, especially in congested traffic that is recurrent. Third, they can provide critical mobility to the elderly and disabled. Fourth, they have the potential of increasing road capacity, saving fuel, and lowering emissions, if automatic steering algorithms are carefully developed. Complementary trends in shared rides and vehicles may lead us from vehicles as an owned product to an on-demand service, and mitigate the need for parking space and change land use patterns, including changes to current zoning codes that often require specific parking requirements per occupant or dwelling type. Additionally, the passenger compartment may be transformed: former drivers may be working on their laptops, eating meals, reading books, watching movies, and/or calling friends—safely. It is estimated that by 2030, the value of global automated car market will be worth $87 billion (LUX Research, 2014).

*Public Sector*

Smart driving technologies will change the landscape of transportation and bring significant potential benefits in safety, mobility and environment. Federal agencies engaged in smart driving technology research, tests and policymaking include FHWA, NHTSA, RITA, FRA, FTA, and MARAD. The following programs were created to promote the collaborative efforts in research, prototyping and tests (USDOT ITS JPO, 2015):

- USDOT connected vehicle safety pilot: the Connected Vehicle Safety Pilot a research program that demonstrates the readiness of DSRC-based connected vehicle safety applications for nationwide deployment. The vision of the Connected Vehicle Safety Pilot program is to test connected vehicle safety applications in real-world driving scenarios in order to determine their effectiveness at reducing crashes and to ensure that the devices are safe and do not unnecessarily distract motorists or cause unintended consequences.
- USDOT ITS JPO connected vehicle pilot deployment: The USDOT's connected vehicle research program is a multimodal initiative to enable safe, interoperable, networked wireless communications among vehicles, infrastructure, and personal communications devices. USDOT expects an initial set of pilot deployments (Wave 1) to begin in Fall 2015, and a second wave (Wave 2) in 2017. Prior to Wave 1, USDOT is sponsoring multiple workshops and other events to assist stakeholder planning.
- Automation program: ITS established an automation program within the overall ITS program. As a first step, the program has developed a 2015-2019 Multimodal Program Plan for Vehicle Automation, a key component of the ITS JPO's ITS Strategic Plan 2015-2019. The program plan establishes the vision, role, and goals, as well as a broad research roadmap for automation research at USDOT.

In 2004, the Defense Advanced Research Projects Agency's (DARPA's) Grand Challenge was launched with the goal of demonstrating AV technical feasibility by challenging participants to navigate a 150-mile route autonomously. While the best team completed just over seven miles, one year later five driverless cars successfully navigated the full route. In 2007, six teams finished the new Urban Challenge, where AVs were required to obey traffic rules, deal with blocked routes, and maneuver around fixed and moving obstacles, together providing realistic, every-day-driving scenarios. Europe's CityMobile2 project is currently demonstrating low-speed fully autonomous transit applications in five cities. Additionally, AVs are becoming increasingly common in other sectors including military, mining, and agricultural. While urban environments pose much greater challenges, these environments can be helpful testing grounds for AV innovation.

States are proceeding with AV-enabling legislation: California, Florida, and Nevada have enacted bills to regulate AV licensing and operation, with instructions to their respective Departments of Motor Vehicles (DMVs) for fleshing out details. Yet some of these efforts are in direct conflict with federal guidance. NHTSA has issued a statement advocating that states should begin establishing procedures for allowing testing on public roads, though should not yet begin licensing AV sales to the general public. In contrast, California has directed its DMV to provide AV licensing requirements by 2015.

*Private Sector*

Over the past few years the automobile and technology industries have made significant leaps in bringing computerization into what has, for over a century, been exclusively a human function: driving. New car models increasingly include features such as adaptive cruise control and parking assist systems that allow cars to steer themselves into parking spaces. Assuming that these technologies become successful and available to the mass market, AVs have the potential to dramatically change the transportation network.

At the September 2012 signing of California's law enabling AV licensure (SB 1298), Google founder Sergey Brin predicted that Americans could be using AVs within five years. Nissan and Volvo both have announced their intentions to have commercially viable autonomous-driving capabilities by 2020 in multiple vehicle models. Assuming an additional five years for prices to drop to allow for some degree of mass-market penetration, AVs may be available on the mass market by 2022 or 2025, approximately two decades after the DARPA Grand Challenge's first successful tests. State DOTs, planners and policymakers need to begin to address the unprecedented issues that AVs could surface, while facilitating owners' adoption rates on incremental improvements.

Google's self-driving cars have driven over 700,000 miles on California public roads, and numerous manufacturers—including Audi, BMW, Cadillac, Ford, GM, Mercedes-Benz, Nissan, Toyota, Volkswagen, and Volvo—have begun testing driverless systems. Semi-autonomous features are now commercially available, including adaptive cruise control (ACC), lane departure warnings, collision avoidance, parking assist systems, and on-board navigation.

### 2.2.2 Barriers

A number of barriers are anticipated to challenge the development and implementation of intelligent driving technologies, especially the Level 3 and Level 4 technologies. The major factors that could hinder technology adoption before its full maturity include:

- **High Cost:** Compared to conventional car, the Level 0 (connected vehicle) and L2 technologies incur extra cost ranging from several hundred to thousands of dollars. For example, an intelligent driving package including radar-based ACC, collision warning and adaptive braking cost about $1,200 as of December 2016. This cost is even higher on L3 and L4 vehicles, because a Lidar system (which is equipped on Google self-driving cars) alone costs thousands of dollars.
- **Security and Privacy:** When vehicles are controlled by computers and connected wirelessly, like other cyber-physical systems, they are vulnerable to attacks, including hacking, and GPS spoofing. Meanwhile, with the smart driving technologies, a large amount of data are generated and collected, through onboard sensors. This data contain location information that could be sensitive, e.g., where a car was last parked and distances traveled as well as time and speed.
- **Operations in Transition Stage:** It is anticipated that when smart driving technologies are adopted, there will be at least one decade when regular cars still run on the road. It is estimated that the average operating life of model year 1990 cars is 16.9 years. When cars of different automation levels co-exist on the road, the problem of how to manage them and ensure equity, efficiency and safety will be paramount.

Other barriers facing the intelligent driving technologies include legislation, liability licensing, and insurance, privacy concerns and social equity. These issues call for targeted policy and legislation.

### 2.2.3 Mainstream Adoption

As this report has indicated, Level 0 and Level 1 technologies are readily available on the market and ready for large-scale deployment. In contrast, Level 3 and Level 4 technologies are facing the most significant barriers and uncertainties. Table 2.3 outlines a forecast of technology development.

**Table 2.3: Forecast of Technology Development Timeline**

| # | Technology | Mainstream adoption | Barriers |
|---|---|---|---|
| 1 | Forward Collision Warning | 2015–2020 | Reliability |
| 2 | Blind Spot Monitoring | 2015–2020 | Cost |
| 3 | Lane Departure Warning | 2015–2020 | Infrastructure |
| 4 | Traffic Sign Recognition | 2015–2025 | Cost, Technology Maturity |
| 5 | Left Turn Assist | 2015–2025 | Cost, Infrastructure |
| 6 | Adaptive Headlight | 2015–2020 | None |
| 7 | Adaptive Cruise Control | 2015–2020 | Cost |
| 8 | Cooperative Adaptive Cruise Control | 2020–2025 | Standard, Cyber-security |
| 9 | Automatic Emergency Braking | 2015–2025 | Cost, Reliability |
| 10 | Lane Keeping | 2015–2020 | Infrastructure |
| 11 | Electric Stability Control | 2010–2011 | None; mandated by NHTSA since 2011 |
| 12 | Parental Control | 2015–2020 | None |
| 13 | Traffic Jam Assist | 2015–2020 | Cost |
| 14 | High Speed Automation | 2015–2025 | Reliability |
| 15 | Automated Assistance in Roadwork and Congestion | 2015–2025 | Infrastructure, Reliability |
| 16 | On-Highway Platooning | 2015–2020 | Infrastructure, Cost |
| 17 | Automated Operation for Military | Unknown | Unknown |
| 18 | Driverless Car | 2015–2030 | Regulation, Liability, Cost, Cyber- security, Infrastructure |
| 19 | Emergency Stopping Assistance | 2015–2025 | Liability |
| 20 | Auto-Valet Parking | 2015–2025 | Infrastructure |

### 2.2.4 Traffic Impact

In general, AVs can reduce travel times through crowd-sourcing-based navigation (smarter route choices), automatic collision reports (e.g., OnStar), & more stable cruising speeds. AVs can also reduce travel time uncertainties via better en-route information (such as construction, incidents, weather events, etc.), dedicated lanes, and less traffic flow breakdown. It is anticipated that they can increase lane and intersection capacity and smooth traffic oscillations in two main ways:

- **Lane capacity:** AVs can use shorter headways through auto-platooning or coordinated adaptive cruise control (CACC) and/or lane centering (in narrower lanes), which translates to higher capacity (1 to 80% increases in effective capacity, with adoption of 10 to 90% CACC).
- **Intersection capacity:** AVs + CVs can anticipate green phases and so make better use of signal time; they can be better coordinated and share scarce intersection space via mini- platoons based on reservation instructions, for specific paths through an intersection at specific times, (up to 95.5% delay reduction as adoption rates hit 100%).Smart driving vehicles can also influence passenger flows, fleet size, and consequently the need for parking spaces.
- **Passenger/person flows:** Smarter vehicles and trip requests can be matched in real time, increasing vehicle occupancies through dynamic ride-sharing (from U.S. current average of just 1.55 persons) and reducing traffic congestion (by reducing VMT per person-mile travelled)
- **Reduced fleet sizes and lower parking demands:** shared driverless fleets are estimated to reduce the demand for vehicles in urban areas by 90 percent (among carsharing fleet members); this will reduce parking loads, freeing up street space for other modes or additional lanes, in some settings.

AVs could also enable ridesharing and travel by those with limited financial means or physical limitation and thus improve the accessibility of mobility-constrained people to goods, services, jobs and medical appointments.

### 2.2.5 Infrastructure Needs

Based on the previous literature synthesis on smart driving technologies, the team produced the following table (Table 2.4) that predicts potential infrastructure needs and associated costs.

**Table 2.4: Infrastructure Needs Evaluation for Different Technologies**

| # | **Technology** | **Infrastructure Need** | **Infrastructure Cost** |
|---|---|---|---|
| 1 | Forward Collision Warning | None | None |
| 2 | Blind Spot Monitoring | None | None |
| 3 | Lane Departure Warning | Lane marks | Low |
| 4 | Traffic Sign Recognition | Traffic sign | Moderate |
| 5 | Left Turn Assist | Lane marks | Low |
| 6 | Adaptive Headlight | None | None |
| 7 | Adaptive Cruise Control | None, possible dedicated lane | Depends |
| 8 | Cooperative Adaptive Cruise Control | None | None |
| 9 | Automatic Emergency Braking | None | None |
| 10 | Lane Keeping | Lane marks | Low |
| 11 | Electric Stability Control | None | None |
| 12 | Parental Control | None | None |
| 13 | Traffic Jam Assist | Lane marks | Low |
| 14 | High Speed Automation | Lane marks, traffic sign | Moderate |
| 15 | Automated Assistance in Roadwork and Congestion | Lane marks, beacons, guide walls | Relatively high |
| 16 | On-Highway Platooning | Lane marks, traffic sign | Moderate |
| 17 | Automated Operation for Military | None | Unknown |
| 18 | Driverless Car | Lane marks, traffic sign, lighting | Relatively high |
| 19 | Emergency Stopping Assistance | None | None |
| 20 | Auto-Valet Parking | Parking facilities | Relatively High |

Many smart driving technologies are decentralized, in the sense that they do not require any communication with the infrastructure (i.e., V2I) to work. In general, under normal operational conditions, certain smart driving technologies, e.g., lane departure warning and lane keeping, will require clear lane marking and traffic signs, because they rely on sensing of these objects to determine the surrounding environment. Other technologies, such as adaptive cruise control and blind spot monitoring, does not require particular infrastructures, because these are vehicle based features and only rely on sensing of surrounding vehicles but not particular infrastructure. The technologies that will require the most infrastructure changes are traffic sign recognition, automated assistance in roadwork and congestion, auto-valet parking and driverless cars.

# Chapter 3. Surveys to Forecast Adoption Rates

Successful implementation of CAV technologies will require public acceptance and adoption of these technologies over time, via CAV purchase, rental, and use. In recent years, many researchers and consulting firms have conducted surveys and focus groups to understand the public perceptions of CAV benefits and limitations. This section first summarizes key findings of these prior public opinion surveys, then goes on to describe findings of surveys conducted under the current project. These studies provide descriptive statistics regarding public awareness, concerns, and expected benefits of smart-vehicle technologies, but none of them could forecast the long-term adoption of CAV technologies. This section also includes the previously developed frameworks to forecast the long-term adoption of new technologies, such as plug-in hybrid electric vehicles (PHEV).

## 3.1 Prior Survey Results

### 3.1.1 Public Opinion Surveys about Adoption of CAVs

Casley et al. (2013) conducted a survey of 467 respondents to understand their opinions about AVs. The results indicate that approximately 30% of respondents were willing to spend more than $5,000 to adopt full automation in their next vehicle purchase and around the same proportion of respondents showed interest in adopting AV technology four years after its introduction in the market. Eighty-two percent of respondents reported safety was the most important factor affecting their adoption of AVs, while 12% said legislation, and 6% said cost.

Begg (2014) conducted a survey of over 3,500 London transport professionals to understand their expectations and issues related to the growth of driverless transportation in London. Eighty-eight percent of respondents expected Level 2 vehicles to be on the road in the U.K. by 2040; 67% and 30% believe the same for Level 3 and Level 4 vehicles, respectively.

Furthermore, approximately 60% of respondents supported driverless trains in London, and the same proportion of respondents expected AVs to be safer than conventional vehicles.

Kyriakidis et al. (2014) conducted a survey of 5,000 respondents across 109 countries by means of a crowdsourced internet survey. The results indicate that respondents with higher vehicle miles traveled and who use the automatic cruise control feature in their current vehicles are likely to pay more for fully automated vehicles. Approximately 20% of respondents showed a WTP of more than $7,000 for Level 4 AVs, and approximately the same proportion of respondents did not want to pay more to add this technology to their vehicle. Most importantly, 69% of respondents expected that fully automated vehicles are likely to gain 50% market share by 2050.

Schoettle and Sivak (2014a) surveyed 1,533 respondents across the U.K., the U.S., and Australia to understand their perceptions of AVs. Results indicate that approximately two-thirds of respondents had previously heard about AVs. When respondents were asked about the potential benefits of Level 4 AVs, 72% expected fuel economy to increase, while 43% expected travel-time savings to increase. Interestingly, 25% of respondents were willing to spend at least $2,000 to add full self-driving automation in the U.S., while the same proportion of respondents in the U.K. and Australia were willing to spend $1,710 and $2,350, respectively. However, around 55% of respondents in each country did not want to pay more to add these technologies. When asked about their potential activities while riding in Level 4 AVs (e.g., working, reading, and talking with friends), the highest proportion of respondents (41%) said they would watch the road even though they would not be driving. The results of one-way analysis of variance indicated that females are more concerned about AV technologies than males.

Underwood (2014) conducted a survey of 217 experts. Eighty percent of respondents had a master's degree, 40% were AV experts, and 33% were CV experts. According to these experts, legal liability is the greatest barrier to fielding Level 5 AVs (full automation without steering wheel), and consumer acceptance is the smallest. Approximately 72% of the experts suggested that AVs should be at least twice as safe as the conventional vehicles before they are authorized for public use. Fifty-five percent of the experts indicated that Level 3 AVs are not practical because drivers could become complacent with automated operations and may not take required actions.

CarInsurance.com's survey of 2000 respondents found that approximately 20% were interested in buying AVs (Vallet, 2013). Interestingly, when respondents were presented with an 80% discount on car insurance for AV owners, 34% and 56% of respondents indicated strong and moderate interest in buying AVs, respectively. When respondents were asked to choose the activities they would like to perform while riding in AVs, the highest share of respondents (26%) chose to talk with friends. Survey results also indicate that approximately 75% of respondents believed that they could drive more safely than AVs. Only 25% would allow their children to go school in AVs, unchaperoned. When asked who they would trust most to deliver the AV technology, the highest proportion (54%) of respondents said traditional automobile companies (e.g., Honda, Ford, and Toyota), instead of technology companies (e.g., Google, Microsoft, Samsung, and Tesla). Seapine Software's (2014) survey of 2,038 respondents indicated that approximately 88% (84% of 18- to 34-year-olds and 93% of 65-year-olds) were concerned about riding in AVs. Seventy-nine percent of respondents were concerned about equipment failure, while 59% and 52% were concerned about liability issues and hacking of AVs, respectively.

J.D. Power (2012) conducted a survey of 17,400 vehicle owners before and after revealing the market price of 23 CAV technologies. Prior to learning about the market price, 37% of respondents showed interest in purchasing the AV technology in next vehicle purchase, but that number fell to 20% after learning that this technology's market price is $3,000. The 18- to 37-year-old male respondents living in urban areas showed the highest interest in purchasing AV technology.

A KPMG (Klynveld Peat Marwick Goerdeler) (2013) focus group study, using 32 participants, notes that respondents became more interested in AVs when they were provided incentives like a designated lane for AVs, and learned that their commute time would be cut in half. In contrast to Schoettle and Sivak's (2014a) findings, the focus group's discussion and participants' ratings for AV technology suggests that females are more interested in these technologies than males. While focus-group females emphasized the benefits of AVs (e.g., mobility for physically challenged travelers), males were more concerned about being forced to follow speed limits. Interestingly, the oldest participants (60 years old+) and the youngest (21 to 34 years old) expressed the highest WTP in order to obtain automation technologies.

Continental (2015) surveyed 1,800 and 2,300 respondents in Germany and the United States, respectively. Approximately 60% of respondents expected to use AVs in stressful driving situations, 50% believed that AVs can prevent accidents, and roughly the same number indicated they would likely engage in other activities while riding in AVs.

Recently, Schoettle and Sivak (2014b) surveyed 1,596 respondents across the U.K., the U.S., and Australia to understand their perceptions of CVs. Surprisingly, only 25% of respondents had heard about CVs. When asked about the expected benefits of CVs, the highest proportion of respondents (85.9%) expected fewer accidents and the lowest proportion (61.2%) expected less distraction for the driver. Approximately 84% of respondents rated safety as the most important benefit of CVs, 10% said mobility, and 6% said environmental benefits. Interestingly, 25% of respondents were willing to spend at least $500, $455, and $394 in the U.S., the U.K., and Australia, respectively, to add CV technology. However, 45.5%, 44.8%, and 42.6% of respondents did not want to pay anything extra to add these technologies in the U.S., the U.K., and Australia, respectively.

### 3.1.2 Anticipating Long-Term Adoption of New Technologies

Vehicle transaction models and simulation frameworks have been increasingly used for forecasting market shares of alternative fuel vehicles (Paul et al., 2011). However, these models are not directly applicable to forecasting the long-term adoption of CAV technologies, but provide a good basis for this new framework. Musti and Kockelman (2010) proposed a vehicle fleet evolution framework to forecast PHEV's and HEV's shares in Austin, Texas, over a 25-year period. They developed a microsimulation framework based on a set of interwoven models (vehicle transaction, vehicle choice, and vehicle usage) for vehicle ownership along with greenhouse gas (GHG) emissions forecasts in Austin. They estimated Austin's highest future PHEV-plus-HEV share (19% by 2034) under a feebate policy scenario. Paul et al. (2011) adopted a similar microsimulation framework to forecast the U.S. vehicle fleet's composition and associated GHG emissions, from 2010 to 2035, under a variety of policy, technology, and gas-price scenarios. Paul et al. (2011) predicted 14.8% as the highest (total) predicted share of PHEV-plus-HEV by 2035, under the gas price of $7 per gallon.

## 3.2 Survey Design and Data Processing

### 3.2.1 Questionnaire Design and Data Acquisition

The team designed and disseminated a Texas-wide survey in June 2015 using Qualtrics, a web-based survey tool. The Survey Sampling International's (SSI, an internationally recognized and highly professional survey firm) continuous panel of respondents served as the respondents for this survey. The Office of Research Support at The University of Texas at Austin processed this study and determined it as "Exempt" from Institutional Review Board[1] (IRB) review (protocol number: 2014-09-0078).

Exploring respondents' preferences for the adoption of emerging vehicle and transport technologies, the survey asked 58 questions, divided into 6 sections. The survey asked respondents about their household's current vehicle inventory (e.g., odometer reading and average miles traveled per year), vehicles sold in the past 10 years, future vehicle preferences (e.g., buying or selling a vehicle, or only adding technology to the existing vehicles), and WTP for various CAV technologies. Respondents were also asked for their opinions related to CAVs (e.g., comfort in allowing vehicle to transmit data to various agencies and the appropriate developers for Level 4 AVs), travel patterns (e.g., using AVs for the long-distance trips and increase in frequencies of long-distance trips due to AVs), and demographics.

[1] IRB reviews research studies to minimize the risks for human subjects, ensure all subjects give their consent and receive full information about risks involved in the research, and aims to promote equity in human subject research.

### 3.2.2 Data Cleaning and Sample Correction

A total of 1,762 Texans completed the survey, but after removing the fast responses and conducting some sanity checks[2], 1,364 responses remained eligible for further analysis. The sample over-represented specific demographic classes, such as female and bachelor degree holders, and under-represented others, such as men who did not complete high school and males 18 to 21 years old. Therefore, the survey sample proportions in three demographic classes or sixty categories (two gender-based, five age-based, and six educational-attainment groups[3]) were scaled using the 2013 American Community Survey's Public Use Microdata Sample (PUMS 2013) for Texas. These scale factors were used as person-level weights to un-bias person-related summary statistics (e.g., binary opinion whether AVs are realistic or not) and model-based parameter estimates.

Similarly, some household groups were under- or over-represented. Thus, household weights were calculated for 3 demographic classes or 65 categories (4 household size groups, 4 household workers groups, and 5 vehicle ownership groups)[4] using PUMS 2013 data. These household weights were used to un-bias household-related (e.g., WTP for new technologies and vehicle transaction decisions) model estimates and summary statistics.

### 3.2.3 Geocoding

To understand the spread of survey respondents across Texas and to account for the impact of built-environment factors (e.g., population density and population below poverty line) on household vehicle transaction and technology adoption decisions, the respondents' home addresses were geocoded using Google Maps' API and spatially joined with Texas's census-tract-level shape file using open-source Quantum GIS. For respondents who did not provide their street address or recorded incorrect addresses, their internet protocol (IP) locations were used as the proxies for their home locations. Figure 3.1 shows the geocoded respondents across Texas, with most respondents living in or around Texas' biggest cities (Houston, Dallas, Fort Worth, San Antonio, and Austin), as expected in a relatively unbiased sample.

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[2] Respondents who completed the survey in less than 13 minutes were assumed to have not read questions thoroughly, and their responses were discarded. Certain other respondents were considered ineligible for further analysis: those younger than 18 years, reporting more workers or children than represented in the household size, having a very old car with all technologies, reporting the same distance of their home from various places (airport and city center, for example), and providing other combinations of conflicting answers.

[3] A category "Master's degree holder female and of age between 18 to 24 year" was missing in the sample data. This category was merged with "Bachelor's degree holder female of age between 18 to 24 year" in the population.

[4] There are 80 combinations of traits (4 x 4 x 5 = 80), but there are only 65 categories because some the categories cannot exist. For example, the number of workers cannot exceed household size. Out of 65 categories, 5 were missing in the sample, and were merged with adjacent categories.

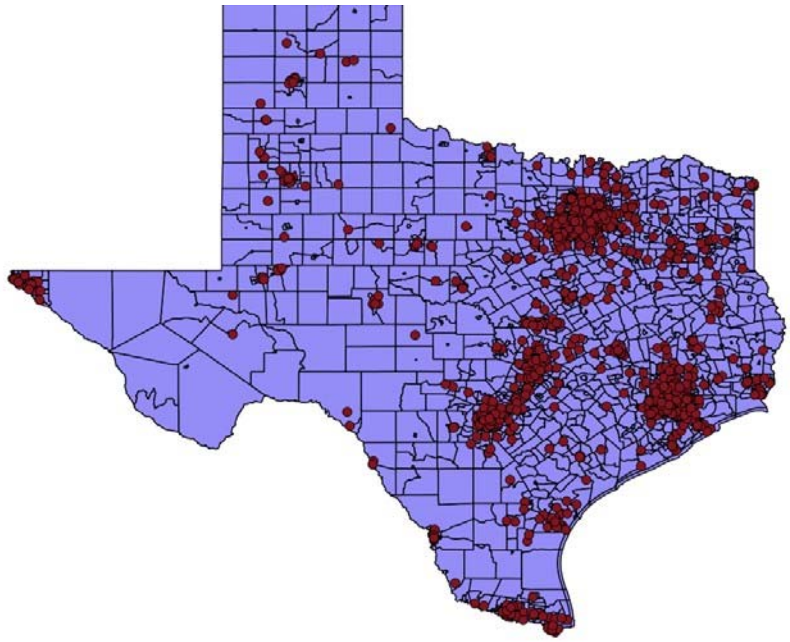

*Figure 3.1: Geocoded Respondents across Texas*

## 3.3 Summary Statistics

### 3.3.1 Level 1 and Level 2 Technologies

Table 3.1 summarizes WTP for, interest in, and current adoption of Level 1 and Level 2 automation technologies[5]. The respondents showed the least interest in traffic sign recognition and left-turn assist technologies. Traffic sign recognition is of no interest to 50.7% of the respondents, and 52.5% noted they are unwilling to pay anything to add this technology to their vehicles. Left-turn assist is slightly more acceptable: 47.2% of the respondents are not interested in it, and 45.1% would not to pay anything for it. Blind-spot monitoring and emergency automatic braking appear to be the two most appealing technologies for Texans. Around half (50.8%) of the respondents are very interested in blind-spot monitoring, only 17.3% are not interested in it, and the smallest proportion of the respondents (only 23.9%) indicate $0 WTP for it. Emergency automatic braking is the second most interesting technology for Texans, with 46.7% of the very-interested respondents, only 23% of the not-interested respondents, and only 28.8% of the respondents with $0 WTP.

Not surprisingly, among these Level 1 and Level 2 automation technologies, electronic stability control (ESC) is the one most expected to be already present in the respondents' vehicles: 21.7% of those who have a vehicle reported having this technology in at least one household vehicle, and it is possible that many respondents are unaware that their vehicles now come equipped with such technology (since ESC has been mandated on all new passenger vehicles in the US since 2012 model year). The second most adopted technology is adaptive cruise control (ACC), with 13.2% of the respondents, who have at least one vehicle, having already adopted this

[5] Level 1 and Level 2 automations are considered together and used interchangeably at a few places, since a combination of Level 1 technologies leads to Level 2 automation.

technology. The least adopted technology is traffic sign recognition, as it is present in only 2% of the respondents' vehicles, while pedestrian detection has a slightly higher rate of adoption, at 3.3%.

The respondents' WTP for Level 1 and Level 2 technology varies significantly[6]. The average WTP (among the respondents who are willing to pay some positive amount for the technology) to add ESC to an existing or a future vehicle exceeded the projected price after five years: $79 (see Table 3.3[7]) versus $70. For every other technology, the average WTP (of the respondents who are ready to pay for the technology) is lower than the estimated future price after five years. For example, average WTP to add emergency automatic braking is $263 versus $320, (the projected price after five years) and for blind-spot monitoring, it is $208 versus $280. The worst ratio of the average WTP to the projected price is for the adaptive headlights: $346 versus $700. Respondents value this technology significantly; in fact, it is the second most valued technology in terms of average WTP (of the respondents who are ready to pay for the technology), but respondents probably believe that the projected price is still too high.

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[6] Before asking a WTP question, respondents were provided with a price forecast for a particular technology. For example, the price forecast for ESC was "Current Price: $100; Price after 5 years: $70; Price after 10 years: $50". It is difficult to estimate the price of a particular Level 1 or Level 2 technology, since these technologies are provided in packages. For example, BMW provides a $1900 package with lane departure warning, forward collision braking, adaptive cruise control, pedestrian detection, and blind-spot monitoring. Thus, after analyzing different packages, current prices for each of these technologies were determined. Subsequently, 30% price reduction in the next 5 years and a 50% price reduction in the next 10 years were considered (with 7% annual price reduction rate) to provide future price estimates of these technologies.

[7] Table 3.3 demonstrates average WTP for CAV technologies. The second column represents average WTP of all respondents, and the third column summarizes the WTP of those who indicated WTP more than $0 for a specific technology.

## Table 3.1: Population-weighted Summaries for Level 1 and Level 2 Technologies ($N_{obs}$=1,364)

| Response Variables | Percentages | Response Variables | Percentages |
|---|---|---|---|
| ***Electronic Stability Control*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 33.3% | Yes | 21.7% |
| Less than $60 | 15.2% | *Interested in Technology* | |
| $60 to $79 | 22.1% | Not interested | 28.6% |
| $80 to $119 | 22.3% | Slightly interested | 41.8% |
| $120 and more | 7.1% | Very interested | 29.6% |
| ***Lane Centering*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 40.5% | Yes | 4.2% |
| Less than $200 | 21.4% | *Interested in Technology* | |
| $200 to $399 | 14.9% | Not interested | 36.8% |
| $400 to $599 | 12.4% | Slightly interested | 39.3% |
| $600 and more | 10.7% | Very interested | 23.9% |
| ***Left-turn assist*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 45.1% | Yes | 4.0% |
| Less than $100 | 15.0% | *Interested in Technology* | |
| $100 to $299 | 23.7% | Not interested | 47.2% |
| $300 to $399 | 8.1% | Slightly interested | 33.6% |
| $400 and more | 8.1% | Very interested | 19.3% |
| ***Cross Traffic Sensor*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 32.3% | Yes | 10.4% |
| Less than $100 | 14.6% | *Interested in Technology* | |
| $100 to $199 | 14.5% | Not interested | 30.5% |
| $200 to $399 | 24.9% | Slightly interested | 38.0% |
| $400 and more | 13.7% | Very interested | 31.6% |
| ***Adaptive Headlights*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 40.3% | Yes | 9.2% |
| Less than $150 | 17.9% | *Interested in Technology* | |
| $150 to $349 | 17.4% | Not interested | 35.3% |
| $350 to $649 | 15.6% | Slightly interested | 37.6% |
| $650 and more | 8.9% | Very interested | 27.1% |

| Response Variables | Percentages | Response Variables | Percentages |
|---|---|---|---|
| ***Pedestrian Detection*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 37.6% | Yes | 3.3% |
| Less than $100 | 15.8% | *Interested in Technology* | |
| $100 to $199 | 13.1% | Not interested | 32.2% |
| $200 to $399 | 24.3% | Slightly interested | 36.8% |
| $400 and more | 9.1% | Very interested | 31.0% |
| ***Adaptive Cruise Control*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 36.6% | Yes | 13.2% |
| Less than $150 | 26.7% | *Interested in Technology* | |
| $150 to $249 | 15.6% | Not interested | 31.9% |
| $250 to $349 | 11.6% | Slightly interested | 36.1% |
| $350 and more | 9.5% | Very interested | 32.0% |
| ***Blind-spot Monitoring*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 23.9% | Yes | 9.7% |
| Less than $150 | 29.3% | *Interested in Technology* | |
| $150 to $249 | 18.8% | Not interested | 17.3% |
| $250 to $349 | 15.3% | Slightly interested | 31.9% |
| $350 and more | 12.8% | Very interested | 50.8% |
| ***Traffic Sign Recognition*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 52.5% | Yes | 2.0% |
| Less than $100 | 15.6% | *Interested in Technology* | |
| $100 to $199 | 10.2% | Not interested | 50.7% |
| $200 to $299 | 10.7% | Slightly interested | 30.8% |
| $300 and more | 11.1% | Very interested | 18.5% |
| ***Emergency Automatic Braking*** | | | |
| *Willingness to Pay to Add* | | *Present in a Vehicle** | |
| Do not want to pay anything | 28.8% | Yes | 5.9% |
| Less than $200 | 25.4% | *Interested in Technology* | |
| $200 to $299 | 18.8% | Not interested | 23.0% |
| $300 to $399 | 14.3% | Slightly interested | 30.3% |
| $400 and more | 12.7% | Very interested | 46.7% |
| *Among the respondents who reported to have at least one vehicle in their households. | | | |

### 3.3.2 Connectivity and Advanced Automation Technologies

Table 3.2 summarizes respondents' WTP to add connectivity, self-parking valet system, and Level 3 and Level 4 automation. It is evident that more than half of the respondents are not ready to pay for any of the advanced automation technology, but comparatively fewer (only around 37.9%) indicated $0 WTP to add connectivity. Among those who are willing to pay for advanced automation, the average WTP for Level 3 automation is $5,551 and for Level 4 automation, it is $14,589 (see Table 3.3). Self-parking valet technology is valued at around $924 (with a simulation-projected price of $1,400 after 5 years, which may be too low [given how complex discerning a proper/legal parking spot can be in many settings]) and connectivity is valued at only $110 (projected price after five years is $140).

**Table 3.2: Population-weighted WTP for Adding Connectivity and Advanced Automation Technologies ($N_{obs}$=1,364)**

| Response Variables | Percentages | Response Variables | Percentages |
|---|---|---|---|
| *WTP for Adding Level 3 Automation* | | *WTP for Adding Self-parking Valet* | |
| Do not want to pay anything | 55.4% | Do not want to pay anything | 51.6% |
| Less than $2,000 | 12.8% | Less than $250 | 13.2% |
| $2,000 to $5,999 | 14.1% | $250 to $1,249 | 19.8% |
| $6,000 to $9,999 | 9.4% | $1,250 to $1,749 | 9.0% |
| $10,000 and more | 8.3% | $1,750 and more | 6.4% |
| *WTP for Adding Level 4 Automation* | | *WTP for Adding Connectivity* | |
| Do not want to pay anything | 57.9% | Do not want to pay anything | 37.9% |
| Less than $6,000 | 14.9% | Less than $75 | 21.2% |
| $6,000 to $13,999 | 9.4% | $75 to $124 | 16.9% |
| $14,000 to $25,999 | 9.8% | $125 to $174 | 11.7% |
| $26,000 and more | 8.0% | $175 and more | 12.3% |

**Table 3.3: Population-weighted Average WTP for Automation Technologies ($N_{obs}$=1,364)**

| Average WTP for Adding Technology | For all Respondents | For those with WTP > 0 |
|---|---|---|
| Electronic Stability Control | $53 | $79 |
| Lane Centering | $211 | $355 |
| Left-turn assist | $123 | $224 |
| Cross Traffic Sensor | $174 | $257 |
| Adaptive Headlights | $207 | $346 |
| Pedestrian Detection | $144 | $231 |
| Adaptive Cruise Control | $128 | $202 |
| Blind-spot Monitoring | $158 | $208 |
| Traffic Sign Recognition | $97 | $203 |
| Emergency Automatic Braking | $187 | $263 |
| Connectivity | $68 | $110 |
| Self-parking Valet | $448 | $924 |
| Level 3 Automation | $2,474 | $5,551 |
| Level 4 Automation | $6,148 | $14,589 |

### 3.3.3 Opinions about CAV Technologies and Related Aspects

Table 3.4 summarizes the respondents' opinions about their own behavior, automation technologies, and related aspects. Most Texans perceive themselves as good drivers (86.5%), enjoy driving a car (75.6%), and tend to wait before adopting new technologies (79.2%). Respondents are indecisive on the topic of whether AVs will drive better than them (around one- third agrees, around one-third disagrees, and the last third has no opinion on this). Around 55.3% of the respondents perceive AVs as a useful advancement in transportation, but 56.3% are scared of them. Only around one-quarter (24.8%) of the respondents have been waiting for AV availability and only 19.8% will be comfortable sending an AV driving on its own, assuming that they as owners are liable for any accident it might cause. 43.8% of the respondents agree with the statement that AVs will be widespread in the future. Around 47% of the respondents think that AVs will function reliably, while 44% believe the idea of AVs is not realistic.

**Table 3.4: Individual-weighted Opinions of Respondents ($N_{obs}$=1,364)**

| Opinions | Agree | Neutral | Disagree |
|---|---|---|---|
| I believe that I am a very good driver myself. | 86.3% | 10.8% | 3.0% |
| I think AVs will drive more safely than my driving. | 34.3% | 31.9% | 33.7% |
| Driving a car is something I enjoy. | 75.6% | 15.3% | 9.2% |
| I generally tend to wait for a new technology if it proves itself. | 79.2% | 13.6% | 7.2% |
| AVs are a useful advance in transportation. | 55.3% | 25.3% | 19.4% |
| The idea of AVs is not realistic. | 44.0% | 25.0% | 31.0% |
| AVs will be a regular mode of transport in 15 years. | 43.8% | 29.4% | 26.8% |
| AVs scare me. | 56.7% | 19.0% | 24.3% |
| I have waited a long time for AVs. | 24.8% | 22.8% | 52.5% |
| I do not think that AVs will function reliably. | 47.0% | 30.2% | 22.8% |
| I would be comfortable in sending my AVs out knowing that I am liable for an accident. | 19.8% | 20.3% | 59.9% |

Table 3.5 summarizes the respondents' opinions about their comfort in allowing their CVs to share information with certain organizations or other vehicles, as well as whom they trust to develop AVs. It is interesting to note that more than half of the respondents (52.7%) are comfortable if their vehicle transmits information to other vehicles, and 46% are comfortable sending information to the vehicle manufacturer. Respondents were most uncomfortable sending information to insurance companies (34.4%) and toll operators (32.5%).

The respondents mostly believe that AVs must be produced by technology companies (63.1%), and luxury vehicle manufacturers (49.5%). Mass-market manufacturers are in third place with support from 45.1% of the respondents. Around 8.2% of the respondents do not trust any company to manufacture AVs, and very few respondents (1%) are unsure.

**Table 3.5: Individual-weighted Opinions about Connectivity and AVs' Production ($N_{obs}$=1,364)**

| **Comfortable in allowing a vehicle to transmit information to…** | **Comfortable** | **Neutral** | **Uncomfortable** |
|---|---|---|---|
| Surrounding vehicles | 52.7% | 17.5% | 29.8% |
| Vehicle manufacturers | 46.0% | 24.9% | 29.1% |
| Insurance companies | 39.9% | 25.8% | 34.4% |
| Transportation planners | 43.4% | 28.2% | 28.4% |
| Toll operators | 37.0% | 30.5% | 32.5% |
| **To develop Level 4 AVs, I would trust:** | **Percentage** | | |
| Technology companies (e.g., Google, Apple, Microsoft, and | 63.1% | | |
| Mass-market vehicle manufacturers (e.g., Toyota and Ford) | 45.1% | | |
| Luxury vehicle manufacturers (e.g., BMW and Mercedes) | 49.5% | | |
| Government agencies (e.g., NASA and DARPA) | 1.1% | | |
| Universities and research institutions | 0.4% | | |
| I would not trust any company to develop a Level 4 AVs. | 8.2% | | |
| Unsure | 1.0% | | |

### 3.3.4 Opinions about AV Usage by Trip Types and Long-distance Travel

Table 3.6 demonstrates the respondents' opinions about AV use for different trip types and long-distance travel. Interestingly, around the same proportion of the respondents reported unwillingness to use AVs for short-distance (39.2%) or long-distance (37.3%) trips (over 50 miles). More than 40% of the respondents reported their willingness to use AVs in their everyday trips; however, only 34.8% plan to use them for their or their children's school trips. In the context of long-distance travel, the highest proportion of the respondents (40.9%) plan to use AVs for trips with one-way distances between 100 and 500 miles. The respondents also believe their average number of long-distance trips will increase by 1.3 per month due to the adoption of AVs.

**Table 3.6: Individual-weighted Summaries for AV Usage by Trip Type ($N_{obs}$=1,364)**

| **I will use AVs during a…** | **Percentage** | **I will use AVs for trips…** | **Percentage** |
|---|---|---|---|
| Work trip | 42.8% | Between 50 and 100 miles | 33.1% |
| School trip | 34.8% | Between 100 and 500 miles | 40.9% |
| Shopping trip | 45.0% | Over 500 miles. | 29.9% |
| Personal business trip | 42.8% | I will not use AVs for such trips. | 37.3% |
| Social or recreational trip | 47.1% | **Average increase in the number of long-distance trips** | |
| I will not use AVs. | 39.2% | Additional number of long-distance trips (per month) | 1.3 |

## 3.4 Forecasting Long-Term Adoption of CAV Technologies

### 3.4.1 Simulation-based Framework

The simulation-based framework that forecasts the long-term adoption of CAV technologies consists of several stages, pursued together at a one-year time step. The first stage is a vehicle transaction and technology adoption model (as shown in Figure 3.2) that simulates the households' annual decisions to sell a vehicle ("sell"), buy vehicles ("buy"), sell a vehicle and buy vehicles ("replace"), add technology to the existing vehicles[8] ("add technology"), and take no action ("do nothing"). A multinomial logit (MNL) model was estimated in BIOGEME (Bierlaire 2003) to determine the probabilities of making these decisions and use these probabilities in the Monte Carlo method to ascertain the vehicle transaction and technology adoption choice of each household after each year. Initial model specifications included all explanatory variables and the MNL model was re-estimated using stepwise elimination by removing the covariate with the lowest statistical significance. Although most of the explanatory variables enjoy a p-value greater than .05 (|t-stat| > 1.96), covariates with p-values lower than 0.32 (which corresponds to a |t-stat| of greater than 1.0) were also kept in the final specification.

McFadden's R-Square[9] and adjusted R-square are calculated to measure the models' goodness of fit. In the case of a "sell" decision[9], the oldest vehicle (within a selling household) is disposed of. In the case of a "buy" decision, it is assumed that a household will buy (or lease) either one or two vehicles, and that each vehicle can be acquired new or used. It is important to determine whether a household purchases a new or used vehicle, since it was assumed that Level 3 and Level 4 automations cannot be retrofitted into used vehicles. Using the survey data, the probability that a household acquiring a vehicle will purchase two vehicles that same year is just 0.065, versus 0.373 to purchase a single. These values were used in Monte Carlo simulation.

Subsequently, connectivity is added to the purchased vehicle if a household's WTP for connectivity is more than its price. If the purchased vehicle is used, then Level 1 and Level 2 automations are added based on the household's total budget for Level 2 technologies, and preferences and WTP for each Level 2 technology (or Level 1 technology, if only one technology is added to the vehicle). As mentioned in Section 5, respondents were also separately asked about WTP for a self-parking valet system[10]; this option is added to the used vehicle if the household's WTP is more than its price. If the purchased vehicle is new and the household's WTP for Level 4 automation is greater than the price of its addition, then Level 4 is added to the new vehicle. Otherwise a similar rule is checked for Level 3 automation. If the condition is met for Level 3, this automation is added to the new vehicle; otherwise a self-parking valet system and Level 1 and Level 2 automations are added to the new vehicle with the same rules as described for the used-vehicle case.

In the case of a "replace" decision, a household is assumed to first choose a "sell" option, followed by a "buy" decision. In the case of an "add technology" decision, if an existing vehicle already has Level 3 or Level 4 automations, then no new technology is added to the vehicle. If this is not the case, then the existing technologies in the vehicle are excluded from the choice set, and a self-parking valet system (if not present in the existing vehicle) and Level 1 and Level 2 automations are added to the existing vehicle with the same rules as described for the used-vehicle case. In the "do nothing" case, all vehicles are retained and no technology is added. If a household does not own a vehicle, but the simulation suggests it choose "sell", "replace", or "add technology" options, the household is forced to pick the "do nothing" option.

Finally, the population-weighted adoption rates of all technologies are extracted after each year. This simulation framework does not consider the changes in household demographics or WTP over time (except the respondent's age, since it is an explanatory variable in the vehicle

[8] This study assumes that the households' WTP for CAV technologies remains the same over the simulation period.
[9] It was assumed that the household sells or disposes only one vehicle at a time
[10] Self-parking valet system was not characterized in any level of automation, but was assumed to be present in any vehicle having Level 3 or Level 4 automation.

transaction and technology adoption model). Integrating these additional household evolution models may improve estimates of CAV technologies' future adoption rates.

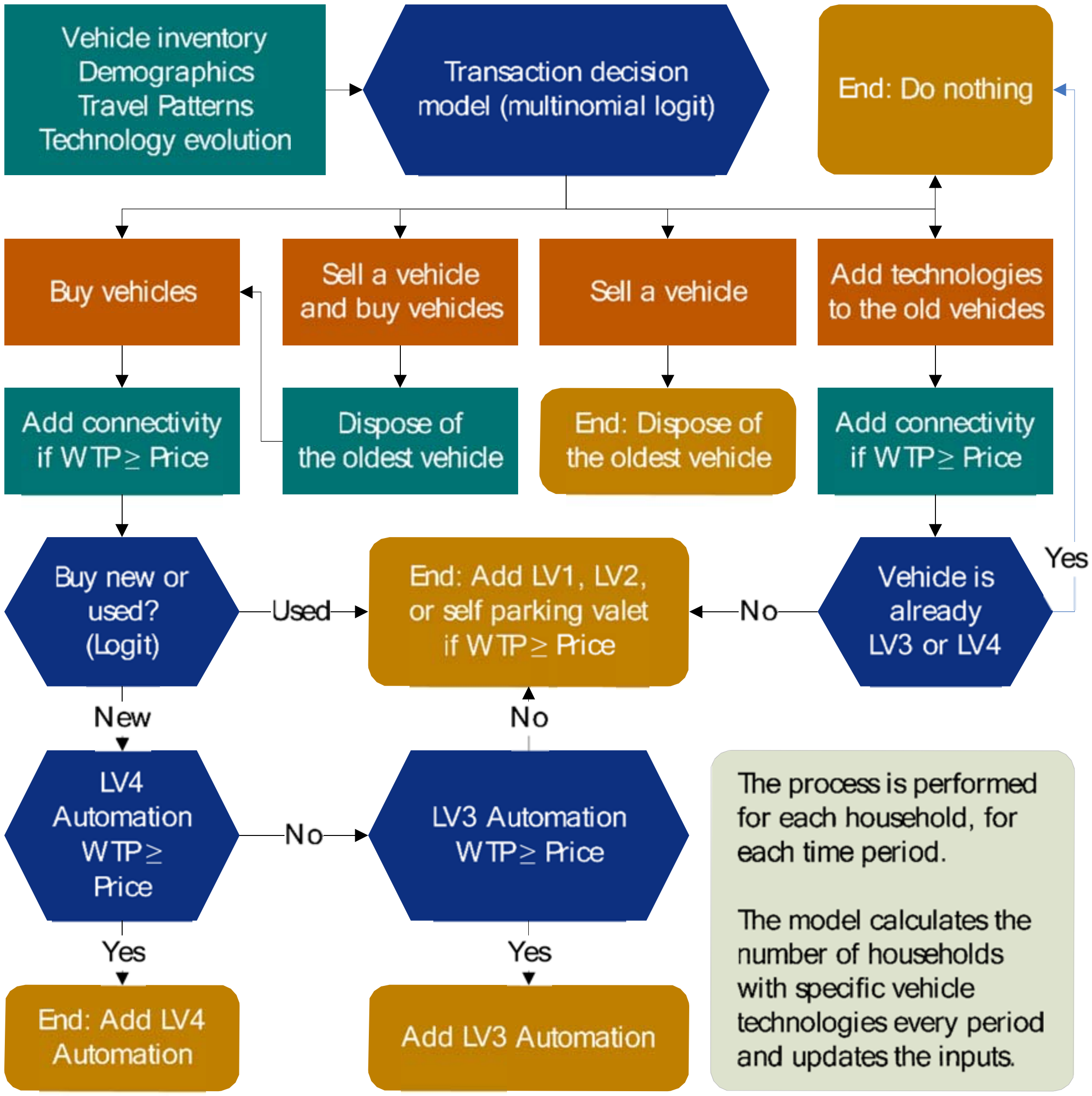



*Figure 3.2: The Transaction Decision Model*

### 3.4.2 Vehicle Transaction and Technology Adoption: Model Specification

Table 3.7 summarizes (with population-weights) person- and household-level variables, geocoded location variables, and transaction decision variables included in the vehicle transaction and technology adoption model.

**Table 3.7: Population-weighted Summary Statistics of Explanatory Variables ($N_{obs}$=1,364)**

| Explanatory Variables | Mean | SD | Min. | Max. |
|---|---|---|---|---|
| *Person Variables* | | | | |
| Age (years) | 46.764 | 16.385 | 21 | 70 |
| Male? | 0.4793 | 0.4998 | 0 | 1 |
| Single? | 0.2956 | 0.4565 | 0 | 1 |
| Bachelor's degree holder? | 0.3752 | 0.4843 | 0 | 1 |
| Full-time worker? | 0.3663 | 0.4820 | 0 | 1 |
| Retired? | 0.1978 | 0.3985 | 0 | 1 |
| Drive alone for work trips? | 0.5832 | 0.4932 | 0 | 1 |
| *Household Variables* | | | | |
| More than 3 members in the household? | 0.2710 | 0.4447 | 0 | 1 |
| More than 1 worker in the household? | 0.3551 | 0.4787 | 0 | 1 |
| Age of the oldest vehicle in the household (in years) | 10.121 | 6.8519 | 0 | 30 |
| Number of vehicles owned by the household | 1.7967 | 0.9853 | 0 | 6 |
| At least one vehicle in the household? | 0.9408 | 0.2360 | 0 | 1 |
| Average vehicle holding time (in years) | 2.3298 | 4.8467 | 0 | 30 |
| Number of vehicles sold in the past 10 years | 0.4335 | 0.6876 | 0 | 5 |
| *Location Variables* | | | | |
| % of families below poverty line in the census tract | 13.152 | 11.125 | 0 | 77 |
| Employed and over 16 years of age (per square mile) | 2,335.8 | 2,412.8 | 1.1917 | 26,021 |
| Population density (per square mile) | 2,993.2 | 3,099.5 | 1.6496 | 32,880 |
| Distance to downtown (from home) is greater than 5 | 0.7147 | 0.4517 | 0 | 1 |
| *Transaction Decisions* | | | | |
| Sell | 0.0358 | 0.1859 | 0 | 1 |
| Replace | 0.2310 | 0.4216 | 0 | 1 |
| Buy | 0.1573 | 0.3642 | 0 | 1 |
| Add technology | 0.1015 | 0.3021 | 0 | 1 |
| Do nothing | 0.4745 | 0.4995 | 0 | 1 |

Table 3.8 shows the MNL model's final specification. The alternative specific constants (ASCs) indicate that, everything else being equal, households have inherent inclination and disinclination for "add technology" and "replace" options. Specifically, older and single individuals with more than one worker in the household, who live farther from downtown in a financially poorer neighborhood (all other attributes remaining constant) are relatively less inclined towards selling their vehicles, but males with more vehicles in the household who drive alone for work are likely to be more inclined to sell.

Bachelor degree holders, full-time workers, and male respondents who drive alone for work, have more vehicles, and more than one worker in the household are more likely (everything else constant) to replace a vehicle, but older respondents are less likely to make this decision. Older and single respondents whose households have higher vehicle holding times and own more vehicles (all other attributes held constant) are less likely to buy vehicles. In contrast, respondents who drive alone to work, have more than three members and one worker in the household, have older vehicles, and have sold more vehicles in the past 10 years are more likely to buy vehicles. It is interesting to note that bachelor's degree holders who drive alone for work trips and live in neighborhoods with higher density of employed individuals are more inclined (everything else constant) towards the "add technology" option than the "do nothing." However, all else being equal, older and single individuals who have older vehicles and live in highly populous neighborhoods are likely to prefer the "do nothing" option over the "add technology." The respondent's age, number of vehicles owned by the household, household's average vehicle holding time, number of vehicles sold in past 10 years, indicator for owning at least one vehicle, and age of the oldest vehicle in the household are annually updated in the simulation.

**Table 3.8: Transaction Decisions (Weighted Multinomial Logit Model Results)**

| **Covariates** | **Coef.** | **T-stat** |
|---|---|---|
| $ASC_{Sell}$ | 0 | -fixed- |
| $ASC_{Replace}$ | -2.83 | -3.9 |
| $ASC_{Buy}$ | 0 | -fixed- |
| $ASC_{Add\ Technology}$ | 0.66 | 1.6 |
| *Sell* | | |
| Age (years) | -0.065 | -7.32 |
| Distance of downtown (from home) is greater than 5 | -0.844 | -2.61 |
| Drive alone for work trips? | 0.361 | 1.06 |
| Male? | 0.589 | 1.74 |
| Number of vehicles owned by the household | 0.706 | 4.38 |
| % of families below poverty line in the census tract | -0.0396 | -2.28 |
| Single? | -0.913 | -2.41 |
| More than 1 worker in the household? | -1.07 | -2.83 |
| *Replace* | | |
| Age (years) | -0.0255 | -4.56 |
| Bachelor's degree holder? | 0.444 | 3.02 |
| Drive alone for work trips? | 0.698 | 3.94 |
| Full-time worker? | 0.266 | 1.63 |
| Male? | 0.317 | 2.24 |
| Number of vehicles owned by the household | 0.154 | 1.72 |
| At least one vehicle in the household? | 1.93 | 2.74 |
| Retired? | 0.821 | 3.15 |
| More than 1 worker in the household? | 0.275 | 1.7 |
| *Buy* | | |
| Age (in years) | -0.0317 | -7.82 |
| Drive alone for work trips? | 0.458 | 2.74 |
| More than 3 members in the household? | 0.451 | 2.81 |
| Age of the oldest vehicle in the household (in years) | 0.0133 | 1.08 |
| Average vehicle holding time (in years) | -0.0325 | -1.38 |

| Covariates | Coef. | T-stat |
|---|---|---|
| Number of vehicles owned by the household | -0.422 | -3.8 |
| Number of vehicles sold in the past 10 years | 0.236 | 1.87 |
| % of families below poverty line in the census tract | 0.0218 | 3.76 |
| Retired? | 0.443 | 1.57 |
| Single? | -0.154 | -0.99 |
| More than 1 worker in the household? | 0.398 | 2.34 |
| *Add technology* | | |
| Age (in years) | -0.0461 | -5.63 |
| Bachelor's degree holder? | 0.235 | 1.19 |
| Drive alone for work trips? | 0.43 | 2.07 |
| Age of the oldest vehicle in the household (in years) | -0.0593 | -3.8 |
| | | |
| Employed over 16 years (per square mile) | 0.000426 | 2.28 |
| Population density (per square mile) | -0.000327 | -2.09 |
| Retired? | 0.978 | 3.03 |
| Single? | -0.346 | -1.53 |
| *Fit statistics* | | |
| Null log-likelihood | -2195.27 | |
| Final log-likelihood | -1676.58 | |
| McFadden's R-square | 0.236 | |
| Adjusted R-square | 0.219 | |
| Number of observations | 1,364 | |

Note: The "do nothing" option is base here.

### 3.4.3 Forecasted Adoption Rates of CAV Technologies under Pricing Scenarios

*Technology Pricing Scenarios*

This simulation forecasts the annual adoption rates[11] of CAV technologies over the next 30 years (2016 to 2045) under different technology pricing scenarios; the subsequent subsection presents the adoption rates every 5 years.

As mentioned earlier, it is difficult to estimate the price of a particular Level 1 or Level 2 technology since automobile companies provide these technologies in packages. Thus, current prices for these technologies are approximately estimated by analyzing packages provided by BMW, Mercedes, and other manufacturers. Prices to add connectivity, Level 3, and Level 4 automation were estimated based on experts' opinions. This simulation assumes that households' WTP to add CAV technologies do not change over the years (and that NHTSA or other agencies do not mandate any of these technologies on new or used vehicles[12]), but rather that adoption

[11] Technology adoption rate means the percentage of the households having a specific technology, among the households who have at least one vehicle.
[12] If CAVs prove quite helpful (to safety, congestion abatement and/or other major public goals), it may be quite likely that some cities or corridors start requiring such technology. Moreover, NHTSA is expected to require connectivity on all new vehicles soon (in year 2020 for light-duty vehicles and 2021 for medium- and heavy-duty vehicles).

occurs as reductions in technology prices take place. Thus, long-term adoption of the technologies is forecast under three annual price reduction rates: 1%, 5%, and 10%. To provide the sense of the future technology prices at different price reduction rates, Table 3.9 shows an example for the annual price reduction rate of 5%.

**Table 3.9: Technology Prices at 5% Annual Price Reduction Rates**

| Technology | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 |
|---|---|---|---|---|---|---|---|
| Electronic Stability Control | 100 | 77.4 | 59.9 | 46.3 | 35.8 | 27.7 | 21.5 |
| Lane Centering | 950 | 735.1 | 568.8 | 440.1 | 340.6 | 263.5 | 203.9 |
| Left-turn assist | 450 | 348.2 | 269.4 | 208.5 | 161.3 | 124.8 | 96.6 |
| Cross Traffic Sensor | 550 | 425.6 | 329.3 | 254.8 | 197.2 | 152.6 | 118.1 |
| Adaptive Headlights | 1,000 | 773.8 | 598.7 | 463.3 | 358.5 | 277.4 | 214.6 |
| Pedestrian Detection | 450 | 348.2 | 269.4 | 208.5 | 161.3 | 124.8 | 96.6 |
| Adaptive Cruise Control | 400 | 309.5 | 239.5 | 185.3 | 143.4 | 111.0 | 85.9 |
| Blind-spot Monitoring | 400 | 309.5 | 239.5 | 185.3 | 143.4 | 111.0 | 85.9 |
| Traffic Sign Recognition | 450 | 348.2 | 269.4 | 208.5 | 161.3 | 124.8 | 96.6 |
| Emergency Automatic Braking | 450 | 348.2 | 269.4 | 208.5 | 161.3 | 124.8 | 96.6 |
| Connectivity | 200 | 154.8 | 119.7 | 92.7 | 71.7 | 55.5 | 42.9 |
| Self-parking Valet | 2,000 | 1,547.6 | 1,197.5 | 926.6 | 717.0 | 554.8 | 429.3 |
| Level 3 Automation | 15,000 | 11,606.7 | 8,981.1 | 6,949.4 | 5,377.3 | 4,160.8 | 3,219.6 |
| Level 4 Automation | 40,000 | 30,951.2 | 23,949.5 | 18,531.6 | 14,339.4 | 11,095.6 | 8,585.6 |

*Overall Comparison of Technology Adoption in Three Pricing Scenarios*

Tables 3.10, 3.11, and 3.12 present the technology adoption rates at 1%, 5%, and 10% price reduction rates, respectively. Substantial differences are visible between the long-term adoption rates (year 2045) of all technologies at the 1% and 5% price reduction rates. However, such differences are not considerable for many technologies at the 5% and 10% price reduction rates. For example, consider the 56.9% versus 59.9% adoption rates for ESC and the 12.6% versus 16.9% adoption rates of Level 3 automation in 2045 at 5% and 10% price reduction rates. This result may have arisen because many households have very low inclination (WTP of $0 or very low) and some have strong preference (higher WTP) for some CAV technologies (please see Section 5 for this discussion). The long-term technology prices at both the 5% and 10% price reduction rates are able to meet the needs of respondents with higher WTP, but are unable to motivate households with very low WTP to adopt many technologies. In the 1% (and rarely in 5% and 10%) price reduction scenario, a minor temporal decrease occurred in the adoption rates of a few technologies. This might have happened because sometimes the effect of a small price reduction may fall below the noise of the simulation (involving random number generation) or households might have sold their vehicles with these technologies in those years.

**Table 3.10: Technology Adoption Rates at 1% Annual Price Reduction Rates**

| Technology | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 |
|---|---|---|---|---|---|---|---|
| Electronic Stability Control | 21.7 | 35.4 | 32.2 | 30.1 | 29.0 | 29.2 | 28.5 |
| Lane Centering | 4.2 | 4.0 | 2.6 | 2.4 | 2.6 | 3.4 | 4.8 |
| Left-turn assist | 4.0 | 8.7 | 8.1 | 7.3 | 7.3 | 7.4 | 12.0 |
| Cross Traffic Sensor | 10.4 | 10.3 | 7.3 | 5.9 | 5.6 | 10.8 | 11.4 |
| Adaptive Headlights | 9.2 | 6.1 | 3.4 | 2.0 | 2.1 | 2.4 | 2.5 |
| Pedestrian Detection | 3.3 | 8.2 | 7.8 | 7.3 | 7.3 | 7.6 | 13.7 |
| Adaptive Cruise Control | 13.2 | 13.2 | 9.7 | 8.7 | 8.5 | 8.3 | 11.6 |
| Blind-spot Monitoring | 9.7 | 14.0 | 11.7 | 11.2 | 10.7 | 10.7 | 15.2 |
| Traffic Sign Recognition | 2.0 | 3.2 | 3.1 | 3.0 | 2.8 | 3.3 | 6.3 |
| Emergency Automatic | 5.9 | 10.4 | 9.4 | 9.0 | 9.2 | 9.8 | 17.4 |
| Connectivity | 0 | 12.1 | 12.5 | 12.5 | 12.5 | 12.4 | 16.9 |
| Self-parking Valet | 0 | 6.1 | 6.3 | 5.9 | 5.9 | 5.9 | 9.2 |
| Level 3 Automation | 0 | 2.0 | 2.4 | 2.6 | 2.9 | 2.4 | 1.7 |
| Level 4 Automation | 0 | 0.4 | 0.4 | 1.2 | 2.5 | 3.1 | 3.4 |

**Table 3.11: Technology Adoption Rates at 5% Annual Price Reduction Rates**

| Technology | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 |
|---|---|---|---|---|---|---|---|
| Electronic Stability Control | 21.7 | 35.1 | 46.8 | 49.5 | 49.3 | 52.7 | **59.9** |
| Lane Centering | 4.2 | 4.4 | 8.4 | 12.8 | 17.9 | 22.7 | 28.6 |
| Left-turn assist | 4.0 | 8.7 | 13.0 | 20.1 | 23.3 | 31.9 | 34.4 |
| Cross Traffic Sensor | 10.4 | 13.1 | 17.7 | 19.5 | 30.5 | 32.6 | 42.7 |
| Adaptive Headlights | 9.2 | 6.0 | 6.4 | 9.3 | 14.7 | 19.9 | 24.4 |
| Pedestrian Detection | 3.3 | 8.8 | 15.7 | 24.6 | 28.7 | 37.0 | 39.5 |
| Adaptive Cruise Control | 13.2 | 12.6 | 16.4 | 23.8 | 29.2 | 29.6 | 36.5 |
| Blind-spot Monitoring | 9.7 | 14.7 | 23.3 | 29.4 | 38.5 | 38.9 | **45.6** |
| Traffic Sign Recognition | 2.0 | 3.7 | 7.1 | 13.4 | 15.1 | 21.0 | **22.7** |
| Emergency Automatic | 5.9 | 11.4 | 19.9 | 30.3 | 35.5 | 44.5 | **47.3** |
| Connectivity | 0 | 12.2 | 22.1 | 31.0 | 40.0 | 40.8 | 46.9 |
| Self-parking Valet | 0 | 6.0 | 12.9 | 17.7 | 23.8 | 23.9 | 27.5 |
| Level 3 Automation | 0 | 1.4 | 3.8 | 4.8 | 6.9 | 8.4 | 12.6 |
| Level 4 Automation | 0 | 1.1 | 3.3 | 5.3 | 8.7 | 11.2 | 15.9 |

**Table 3.12: Technology Adoption Rates at 10% Annual Price Reduction Rates**

| Technology | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 |
|---|---|---|---|---|---|---|---|
| Electronic Stability Control | 21.7 | 43.7 | 49.7 | 58.9 | 59.6 | 58.7 | **56.9** |
| Lane Centering | 4.2 | 8.3 | 17.7 | 26.9 | 35.1 | 39.2 | 42.3 |
| Left-turn assist | 4.0 | 12.2 | 21.9 | 31.4 | 34.2 | 43.4 | 44.6 |
| Cross Traffic Sensor | 10.4 | 14.3 | 28.2 | 39.8 | 46.6 | 51.9 | 55.1 |
| Adaptive Headlights | 9.2 | 7.8 | 14.1 | 23.3 | 32.4 | 34.8 | 46.0 |
| Pedestrian Detection | 3.3 | 13.5 | 26.5 | 38.8 | 41.0 | 50.4 | 51.3 |
| Adaptive Cruise Control | 13.2 | 18.9 | 28.2 | 35.9 | 43.4 | 43.4 | 47.4 |
| Blind-spot Monitoring | 9.7 | 22.1 | 36.5 | 45.1 | 52.7 | 53.8 | **59.4** |
| Traffic Sign Recognition | 2.0 | 6.4 | 13.8 | 21.7 | 25.3 | 36.4 | **38.4** |
| Emergency Automatic | 5.9 | 17.3 | 32.6 | 45.8 | 49.2 | 58.9 | **59.4** |
| Connectivity | 0 | 20.6 | 36.7 | 45.3 | 50.8 | 51.7 | 57.9 |
| Self-parking Valet | 0 | 12.6 | 21.1 | 25.2 | 30.7 | 29.9 | 34.8 |
| Level 3 Automation | 0 | 2.2 | 6.2 | 10.7 | 13.5 | 14.7 | 16.9 |
| Level 4 Automation | 0 | 2.3 | 6.5 | 13.9 | 23.0 | 33.1 | 38.5 |

*Adoption Rates of Level 1 and Level 2 Technologies*

Traffic sign recognition is the least adopted Level 1 technology in 2015 and is anticipated to remain least adopted, with adoption rates of 22.7% and 38.4%, in 2045 at the 5% and 10% price reduction rates, respectively. ESC is the most adopted Level 1 technology in 2015 and, not surprisingly, it is expected to remain either the most or second-most adopted technology (with adoption rates of 59.9% and 56.9%) in 2045 at 5% and 10% price reduction rates, respectively. Section 5 suggests that emergency automatic braking and blind-spot monitoring are the two most interesting Level 1 technologies for Texans. It is interesting to note that both are forecast to be the most adopted technologies in 2045 at the 10% price reduction rate, with an adoption rate of 59.4%. These technologies are anticipated to be the second- and third-most adopted Level 1 technologies (after ESC—which is now mandated on all new passenger vehicles and so will probably rise to 100% by 2040) in 2045 at 5% price reduction rate, with adoption rates of 47.3% and 45.6%. Pedestrian detection is the second-least adopted technology in 2015, but is expected to be the fifth-most adopted Level 1 technology (out of 10) in 2045 at price reduction rates of 5% and 10%, and adoption rates of 39.5% and 51.3%.

*Adoption Rates of Connectivity and Advanced Automation Technologies*

In 2045, the Level 4 automation adoption rate (38.5%) at a 10% price reduction rate is approximately 2.4 times the adoption rate (15.9%) at a 5% price reduction rate. With 5% and 10% annual price reduction rates, Level 4 automation cost in 2045 would be around \$8590 and \$1700, respectively. This substantial price difference somewhat justifies this anticipated jump in the Level 4 automation's adoption rate at the 10% price reduction rate, relative to 5%. The adoption rates of connectivity technology (46.9% and 57.9%) are close to the adoption rates of the second-most adopted (47.3% and 56.9%) Level 1 technologies in 2045, at price reduction rates of 5% and 10%. At a 10% annual price reduction rate, the anticipated price to add Level 3 automation would be around \$640 in 2045, but still has the adoption rate of only 16.9%. Irrespective of price reduction rate, more than 50% of respondents would not add advanced automation technologies in the future, since they have WTP of \$0 to add them.

# Chapter 4. Traffic Impacts of Connected and Automated Vehicles

This chapter describes analyses of the traffic impacts of connected and automated vehicles under multiple scenarios. Section 4.1 describes how automated vehicles can be integrated into the traditional four-step planning process, including mode and route choice, using static traffic assignment. Section 4.2 shows how dynamic traffic flow models can represent capacity increases from closer following headways and reservation-based “smart intersection” control. Section 4.3 describes two traffic simulation models developed in this research project: the Autonomous Intersection Management microsimulator and a simulation-based dynamic traffic assignment application, as well as results from simulating arterial, freeway, and city networks. Finally, Section 4.4 discusses the traffic impacts of shared automated vehicles.

## 4.1 Static Four-Step Planning for Autonomous Vehicles

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

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

### 4.1.1 Methodology

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

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

*Assumptions*

Because AVs are still in the early stages of testing, experimental data on AV owner behavior and AV improvements in traffic network capacity is not available. Studies such as Dresner and Stone (2004, 1999) have predicted significant improvements in intersection flow, but link capacity changes, if any, have not been studied. Therefore, we make the following assumptions about traveler behavior and capacity:

1. AV market penetration will occur over a number of years as the purchase price gradually becomes viable for travelers of all incomes. Therefore, our model is built on the four-step planning model, which is often used for long-term predictions. A long-term model may be useful to practitioners forecasting the impact of AVs in 20- or 30-year planning models.
2. AV drivers have the option of parking (with a possible parking fee) or sending their AV back to the origin and incurring fuel costs. Although activity-based models (1999) may predict additional utility benefits by making the AV available to other travelers in the household, techniques to model such benefits in the four-step planning model are less clear. Repositioning to alternate parking locations other than the origin for a reduced parking cost is also a realistic option. However, without parking cost data, modeling the utility resulting from parking at different locations is difficult. This results in three mode options: parking, repositioning, and transit. A nested logit model is used to decide between driving and transit, and parking and repositioning.
3. Travelers seek to minimize a generalized cost of time, fuel, and tolls/parking fees. AVs are assumed to choose a route that minimizes this combined cost function, including fuel consumption. Travelers are divided into value-of-time (VOT) classes, and VOT is used to convert travel time to units of money. Incorporating fuel consumption into route choice, or "eco-routing", has been previously studied by Rakha et al. (2012), and AV routing algorithms could incorporate eco-routing technology. Although requiring travelers to choose a VOT for their trip routing may seem restrictive, airlines already do this through their cost index.
4. An STA model is used with four-step planning. Although Tung et al. (2010) and Duthie et al. (2013) have incorporated dynamic traffic assignment (DTA) into the four-step model, without literature on modifying the greater detail in DTA (such as intersection dynamics) for AVs, DTA could easily be less accurate. Additionally, trip distribution and mode choice have potential errors due to the possible behaviors of AV drivers. DTA is more sensitive

to demand and departure time variability, and may exacerbate any errors in demand predictions. Furthermore, DTA also requires more computational resources. Therefore, a STA model, which is commonly used with the four-step model, was chosen for this study.

5. The shorter reaction times and greater precision of AVs are assumed to reduce the necessary following distance and correspondingly increase the jam density. Link jam density is then a function of the proportion of AVs on the link. Capacity is assumed to be linearly related to jam density, as in Greenshields' (1935) model, to predict the increase in capacity as a function of AV proportion. This relationship was chosen because although AVs may have the reaction time to support minimal headways at any speed, the vehicle may not have the braking authority to match maximum braking behavior of the vehicle ahead. Therefore, as speed increases, headways must increase as well, even for AVs. Although Greenshields' relationship is designed for use with hard capacities in DTA as opposed to the "capacity" of the Bureau of Public Roads (BPR) function, it is used here only to scale the original capacities in the static network. In the absence of studies estimating roadway capacity improvement as a function of AV proportion, we believe this assumption is reasonable. Greenshields's model also results in the favorable property of the travel time function being monotone increasing with respect to increases in AV flow (despite increases in capacity).

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

*Impedance Function*

The computer precision and reaction times of AVs allows reduction of headways while maintaining safety in the event of sudden deceleration of the vehicle ahead. These reduced headways increase density, permitting greater roadway capacity. The travel time is given by

$$t_{ij}(\mathbf{x}_{ij}) = \hat{t}_{ij}\left(1 + \alpha_{ij}\left(\frac{\sum_{y \in Y} x_{ij}^{y}}{Q_{ij}(\mathbf{x}_{ij})}\right)^{\beta_{ij}}\right) \tag{4.1}$$

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

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

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

$$\frac{\partial t_{ij}}{\partial x_{ij}^{y}} = \hat{t}_{ij}\alpha_{ij}\beta_{ij}\left(\begin{array}{c}\left(\sum_{y'\in Y} x_{ij}^{y'}\right)^{\beta_{ij}-1}\left(\frac{1}{Q_{ij}(\mathrm{x}_{ij})}\right)^{\beta_{ij}} - \\ \left(\sum_{y'\in Y} x_{ij}^{y'}\right)^{\beta_{ij}}\left(\frac{1}{Q_{ij}(\mathrm{x}_{ij})}\right)^{\beta_{ij}+1}\frac{\partial Q_{ij}(\mathrm{x}_{ij})}{\partial x_{ij}^{y}}\end{array}\right) \tag{4.2}$$

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

$$Q_{ij}(\mathbf{x}_{ij}) > \left(\sum_{y'\in Y} x_{ij}^{y'}\right)\frac{\partial Q_{ij}(\mathbf{x}_{ij})}{\partial x_{ij}^{y}} \tag{4.3}$$

Equation (4.3) implies that capacity must exceed the change in capacity due to additional $x_{ij}^{y}$ flow; otherwise $\frac{\sum_{y'\in Y} x_{ij}^{y'}}{Q_{ij}(\vec{x}_{ij})}$ may decrease resulting in a decrease in $t_{ij}(\mathbf{x}_{ij})$.

A capacity function based on the well-known Greenshields' (1935) speed-density relationship and a jam density function increasing in the proportion of AVs is shown to satisfy equation (4.3) under reasonable assumptions. Greenshields' relationship predicts

$$\mathscr{v}_{ij} = \hat{\mathscr{v}}_{ij}\left(1 - \frac{k_{ij}}{K_{ij}}\right) \tag{4.4}$$

where $\mathscr{v}_{ij}$ is vehicle speed, $\hat{\mathscr{v}}_{ij}$ is free-flow speed, $k_{ij}$ is density, and $K_{ij}$ is jam density on link $[i,j]$. Based on equation (4.4), capacity is $Q_{ij} = \frac{K_{ij}\hat{\mathscr{v}}_{ij}}{4}$, a linear function of jam density. Therefore $Q_{ij}(\vec{x}_{ij})$ is also assumed to be a linear function of jam density:

$$Q_{ij}(\mathbf{x}_{ij}) = \rho K_{ij}(\mathbf{x}_{ij}) \tag{4.5}$$

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

$$K_{ij}(\mathbf{x}_{ij}) = \frac{1}{\zeta_{\mathrm{HV}}}\left(\frac{\sum_{y\in Y}\left(x_{ij}^{y}(1-\xi_{\mathrm{AV}}^{y})\right)}{\sum_{y\in Y}\left(x_{ij}^{y}\right)}\right) + \frac{1}{\zeta_{\mathrm{AV}}}\left(\frac{\sum_{y\in Y}\left(x_{ij}^{y}(\xi_{\mathrm{AV}}^{y})\right)}{\sum_{y\in Y}\left(x_{ij}^{y}\right)}\right) \tag{4.6}$$

The capacity function defined by equations (4.5) and (4.6) is shown to be monotone increasing with respect to any $x_{ij}^{y}$ under the assumption that $2\zeta_{\mathrm{AV}} > \zeta_{\mathrm{HV}}$. This assumption is reasonable considering highway vehicle spacing at jam density was estimated at $\zeta_{\mathrm{HV}} = 27.3$ feet for one city by Van Aerde and Rakha (1995), and Elefteriadou et al. (1997) suggested $\zeta_{\mathrm{AV}} > 17$ feet length for a passenger car equivalent, which is a lower bound on spacing.

*Proof.* Since $2\zeta_{\mathrm{AV}} > \zeta_{\mathrm{HV}}$, $\zeta_{\mathrm{AV}} > \zeta_{\mathrm{HV}} - \zeta_{\mathrm{AV}}$ and $\zeta_{\mathrm{AV}}\sum_{y\in Y} x_{ij}^{y} > (\zeta_{\mathrm{HV}} - \zeta_{\mathrm{AV}})\sum_{y\in Y} x_{ij}^{y}$. Since $\zeta_{\mathrm{HV}} \geq \zeta_{\mathrm{AV}}$,

$$\sum_{y\in Y}(\zeta_{\mathrm{AV}}x_{ij}^{y}\xi_{\mathrm{AV}}^{y}) + \sum_{y\in Y}(\zeta_{\mathrm{HV}}x_{ij}^{y}(1-\xi_{\mathrm{AV}}^{y})) > (\zeta_{\mathrm{HV}} - \zeta_{\mathrm{AV}})\sum_{y\in Y} x_{ij}^{y} \tag{4.7}$$

Since capacity can be rewritten as

$$Q_{ij}(\mathbf{x}_{ij}) = \rho\frac{1}{\zeta_{\mathrm{HV}}\zeta_{\mathrm{AV}}}\frac{1}{\sum_{y\in Y} x_{ij}^{y}}\left(\sum_{y\in Y}(\zeta_{\mathrm{HV}}x_{ij}^{y}(1-\xi_{\mathrm{AV}}^{y})) + \sum_{y\in Y}\left(\zeta_{\mathrm{AV}}x_{ij}^{y}\xi_{\mathrm{AV}}^{y}\right)\right) \tag{4.8}$$

then

$$\frac{\partial Q_{ij}(\mathbf{x}_{ij})}{\partial x_{ij}^{y}} = \rho\frac{1}{\zeta_{\mathrm{HV}}\zeta_{\mathrm{AV}}}\left(\begin{array}{c}\frac{1}{\sum_{y\prime\in Y}x_{ij}^{y\prime}}((1-\xi_{\mathrm{AV}}^{y})\zeta_{AV}+\xi_{\mathrm{AV}}^{y}\zeta_{\mathrm{HV}})-\\ \frac{1}{\left(\sum_{y\prime\in Y}x_{ij}^{y\prime}\right)^{2}}\left(\sum_{y\prime\in Y}(\zeta_{\mathrm{HV}}x_{ij}^{y\prime}(1-\xi_{\mathrm{AV}}^{y}))+\sum_{y\prime\in Y}\left(\zeta_{\mathrm{AV}}x_{ij}^{y\prime}\xi_{\mathrm{AV}}^{y}\right)\right)\end{array}\right) \tag{4.9}$$

$Q_{ij}(\mathbf{x}_{ij}) > \left(\sum_{y\prime\in Y} x_{ij}^{y\prime}\right)\frac{\partial Q_{ij}(\vec{x}_{ij})}{\partial x_{ij}^{y}}$ simplifies to

$$\sum_{y\prime\in Y}\left(\zeta_{\mathrm{AV}}x_{ij}^{y\prime}\xi_{\mathrm{AV}}^{y\prime} + \sum_{y\prime\in Y}(\zeta_{\mathrm{HV}}x_{ij}^{y\prime}(1-\xi_{\mathrm{AV}}^{y\prime}))\right) > \sum_{y\prime\in Y} x_{ij}^{y\prime}(\zeta_{\mathrm{HV}}-\zeta_{\mathrm{AV}}) \tag{4.10}$$

which is satisfied because equation (4.7) is true.

*Fuel Consumption*

To incorporate the multiple types of costs incurred by different modes, such as transit fees and travel time, a generalized cost function is required. Monetary fees and travel time do not fully encompass the cost of an AV making a round trip instead of a one-way trip with parking. The associated cost to the traveler of the AV's return leg is not travel time (for the traveler is not in the vehicle), and road tolls can be avoided by route choice. However, regardless of the route, the return trip incurs additional fuel consumption. Therefore, the fuel consumption function found by Gardner et al. (2013), based on a regression equation from MOVES (2009) data, was used:

$$F_{ij}(v_{ij}) = 14.58(v_{ij})^{-0.6253} \tag{4.11}$$

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

$$F_{ij}(t_{ij}) = \frac{L_{ij}}{36.44\ \mathrm{kW/gal}}\left(14.58\left(\frac{L_{ij}}{t_{ij}}\right)^{-0.6253}\right) \tag{4.12}$$

where 36.44 kW/gal is the energy content of gasoline (A. F. D. Center).

*Generalized Cost*

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

$$c_{ij}^{y,\mathrm{DR}} = \nu_y t_{ij}(\mathbf{x}_{ij}) + \gamma F_{ij}\left(t_{ij}(\mathbf{x}_{ij})\right) + \tau ij \tag{4.13}$$

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

$$C_{rs}^{y,\mathrm{PK}}(\pi) = \varsigma_s^{\mathrm{PK}} + \sum_{(i,j)\in\pi} C_{ij}^{y,\mathrm{DK}}(\mathbf{x}_{ij}) \tag{4.14}$$

where $\pi$ is the route. Other per-mile costs could be incorporated as a fixed cost per link.

For the return leg of AV round-trips, with no passenger, travel time is not a factor, so the notation $c_{ij}^{0,\mathrm{DR}}$ with $\nu_0 = 0$ is used to denote the cost of driving with 0 VOT. Cost of an AV round-trip, using path $\pi_1$ for travel from $r$ to $s$ and path $\pi_2$ for travel from $s$ to $r$, is

$$C_{rs}^{y,\mathrm{AV}}(\pi_1, \pi_2) = \sum_{(i,j)\in\pi_1} C_{ij}^{y,\mathrm{DR}}(\mathbf{x}_{ij}) + \sum_{(i,j)\in\pi_2} C_{ij}^{0,\mathrm{DR}}(\mathbf{x}_{ij}) \tag{4.15}$$

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

$$c_{ij}^{y,\mathrm{TR}}(\mathbf{x}_{ij}) = \nu_y t_{ij}(\mathbf{x}_{ij}) \tag{4.16}$$

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

$$C_{rs}^{y,\mathrm{TR}}(\pi) = \varsigma_{rs}^{\mathrm{TR}} + \sum_{(i,j)\in\pi} C_{ij}^{y,\mathrm{TR}}(\mathbf{x}_{ij}) \tag{4.17}$$

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

### 4.1.2 Model Formulation

The commonly used four-step model was modified to incorporate AV round trips. The latter three steps incorporate a feedback element for convergence to a stable solution. The following subsections discuss each step in greater detail. Multi-class traffic assignment is formulated in Section 15.2.4.

*Trip Generation*

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

*Trip Distribution*

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

$$C_{rs}^{y} = \begin{cases} \min\{C_{rs}^{y,\mathrm{PK}}, C_{rs}^{y,\mathrm{TR}}, C_{rs}^{y,\mathrm{AV}}\} & \text{if } \xi_{\mathrm{AV}}^{y} = 1 \\ \min\{C_{rs}^{y,\mathrm{PK}}, C_{rs}^{y,\mathrm{TR}}\} & \text{otherwise} \end{cases} \tag{4.18}$$

Then

$$d_{rs}^{y} = \eta_{r}^{y} \mu_{s}^{y} P_{r}^{y} A_{s}^{y} \phi\left(C_{rs}^{y}\right) \tag{4.19}$$

where $\phi(\cdot)$ is a decreasing friction function, $\eta_{r}^{y} = \frac{1}{\sum_{s \in Z} \mu_{s}^{y} A_{s}^{y} \phi(C_{rs}^{y})}$, and $\mu_{s}^{y}$ is adjusted iteratively to $\frac{1}{\sum_{r \in Z} d_{rs}^{y}}$ for consistency with productions and attractions, $\sum_{r \in Z} \mathbf{P}_{\mathrm{r}} = \sum_{s \in Z} \mathbf{A}_{\mathrm{s}} = \sum_{r \in Z} \sum_{s \in Z} \mathbf{d}_{\mathrm{rs}}$.

*Mode Choice*

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

Mode-specific trips per class are therefore defined as

$$d_{rs}^{y,\mathrm{TR}} = \begin{cases} \frac{\exp\left(\psi^{\mathrm{TR}} - c_{rs}^{y,\mathrm{TR}}\right)}{\exp\left(\min\{\psi^{\mathrm{AV}} - c_{rs}^{y,\mathrm{AV}}, -c_{rs}^{y,\mathrm{PK}}\}\right) + \exp\left(\psi^{\mathrm{TR}} - c_{rs}^{y,\mathrm{TR}}\right)} & \text{if } \xi_{\mathrm{AV}}^{y} = 1 \\ \frac{\exp\left(\psi^{\mathrm{TR}} - c_{rs}^{y,\mathrm{TR}}\right)}{\exp\left(-c_{rs}^{y,\mathrm{PK}}\right) + \exp\left(\psi^{\mathrm{TR}} - c_{rs}^{y,\mathrm{TR}}\right)} & \text{otherwise} \end{cases} \tag{4.20}$$

$$d_{rs}^{y,\mathrm{AV}} = \begin{cases} \frac{\exp\left(\psi^{\mathrm{AV}} - c_{rs}^{y,\mathrm{AV}}\right)}{\exp\left(\psi^{\mathrm{AV}} - c_{rs}^{y,\mathrm{AV}}\right) + \exp\left(-c_{rs}^{y,\mathrm{PK}}\right)} & \text{if } \xi_{\mathrm{AV}}^{y} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4.21}$$

$$d_{rs}^{y,\mathrm{PK}} = d_{rs}^{y} - d_{rs}^{y,\mathrm{TR}} - d_{rs}^{y,\mathrm{AV}} \tag{4.22}$$

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

$$d_{sr}^{0,\mathrm{AV}} = \sum_{y \in Y} d_{rs}^{y,\mathrm{AV}} \tag{4.23}$$

*Traffic Assignment*

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

Nevertheless, this issue is not unique to this model, but common to all models incorporating multiple discrete VOT classes.

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

$$\sum_{(i,j)\in E} \mathbf{c}_{ij}^{\mathrm{DR}}(\mathbf{x}^*) \cdot (\mathbf{x} - \mathbf{x}^*) \geq 0 \tag{4.24}$$

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

$$\begin{aligned} \mathbf{x}_{ij} &= \sum_{\pi\in\Pi} \delta_{ij}^{\pi} \mathbf{h}_{\pi} && \forall (i,j) \in E \\ \mathbf{h}_{\pi} &\geq \mathbf{0} && \forall \pi \in \Pi \\ \mathbf{d}_{rs}^{DR} + \mathbf{d}_{rs}^{AR} &= \sum_{\pi\in\Pi_{rs}} \mathbf{h}_{\pi} && \forall (r,s) \in Z^2 \end{aligned} \tag{4.25}$$

$x^*$ satisfies user equilibrium (UE) due to Nagurney and Dong's proof (2002) on a more general form of this VI incorporating elastic demand and OD disutility. Due to the special behaviors of AVs, we include only assignment in the VI and solve trip distribution and mode choice separately as in the four-step model.

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

$$\sum_{(i,j)\in E} \sum_{y\in Y} c_{ij}^{y}\left(\lambda \mathbf{x}_{ij}^* + (1-\lambda)\mathbf{x}_{ij}\right)\left(x_{ij}^{y\,*} - x_{ij}^{y}\right) = 0 \tag{4.26}$$

where $x^*$ is the search direction for $\lambda$. The algorithms for multi-class VI formulations of traffic assignment studied by Nagurney and Dong (2002) and Marcott and Wynter (2004) may improve convergence. Optimal convergence of traffic assignment is not a major focus of this study, and a specific algorithm is not a requirement of the model.

*Feedback Algorithm*

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

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

$$\mathbf{d}_{rs}(n+1) = \frac{1}{n+1}\mathbf{d}_{rs}^*(n+1) + \frac{n}{n+1}\mathbf{d}_{rs}(n) \tag{4.27}$$

$$\mathbf{d}_{rs}^{m}(n+1) = \frac{1}{n+1}(\mathbf{d}_{rs}^{m})^*(n+1) + \frac{n}{n+1}\mathbf{d}_{rs}^{m}(n) \tag{4.28}$$

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

$$RMSE^{d} = \sqrt{\frac{\sum_{r\in Z}\sum_{s\in Z}\sum_{y\in Y}\sum_{m\in M}\left(d_{rs}^{y,m}(n+1)-d_{rs}^{y,m}(n)\right)^{2}}{|Z^{2}\times Y\times M|}} \tag{4.29}$$

*Summary*

This section developed an initial model to analyze the impact of AV availability on AM peak transit demand. AVs allow the option of a drop-off and return trip to avoid parking costs, incurring only additional fuel consumption, so a generalized cost function of travel time, monetary fees, and fuel was created to model the cost of a trip. On the other hand, AV use increases road capacity, reducing travel times. This inspired a jam density function of the proportion of AVs on the road, with capacity assumed to be a linear function of jam density in accordance with Greenshields speed-flow density relationship. The resulting travel time function was proven to be monotone increasing for the specific jam density function used.

### 4.1.3 Roadway Capacity Improvement

CAVs have the potential to improve the capacity of the roads people are using. As for a typical highway, HVs provide a maximum throughput of about 2,200 vehicles per hour per lane, only 5% of utilization of the roadway space (2012). AVs, replacing drivers, can increase capacity by shortening vehicle- following gaps and narrowing lanes for light duty vehicles based on more accurate steering (2012). A similar conclusion is reached in the research of Pinjari et al. (2013), which asserts that AVs can allow for much shorter perception and reaction times, smoother braking, and shortening of vehicle-following gaps even at high speeds by sensing and anticipating the lead vehicles braking actions and acceleration/deceleration decisions better than human drivers. The capacity improvement stemming from AV technologies has been investigated by many researchers. Vehicle-to-vehicle (V2V) communication, particularly cooperative adaptive cruise control (CACC), is another critical technology for network improvement. Tientrakool et al. (2011) conducted simulations to investigate the influence of CACC on highway capacity. Their results indicated that CACC can increase a highway capacity, of 2,868 vehicles per hour per lane to 10,720 vehicles per hour per lane, when 100% are communicating vehicles and the speed of vehicles is fixed at 100 km/h—which is a capacity improvement of about 3.7 times. Xu et al. (2002) adopted three different simulation models of travel behavior to study the capacity improvement of CACC. Their study indicated that 100% CACC can provide a 120% improvement compared with manual driving. Although many researchers have obtained simulation results confirming the capacity improvements made possible by CAV technologies, their results are inconsistent because they are based on varying rates of implementation. For example, by assuming full or partial vehicle automation, Childress et al. (2014) applied a 30% increase of all freeway and major arterial capacities to analyze the travel demand model based on the Puget Sound regional area. Gucwa (2014) adopted capacity improvement of 0%, 10% and 100% to estimate the travel behavior in the context of the Bay Area Metropolitan agent-based activity model. To anticipate the travel impact of AVs in Metro Atlanta, Kim et al. (2015) applied a 50% increase in roadway capacity to their activity-based model. Levin and Boyles (2015) proposed a heuristic model, based on Greenshield's model, to scale capacity with the proportion of AVs.

Given the uncertainty of the capacity improvement based on CAV technologies and inconsistent results from the research cited above, it is essential to incorporate a range of outcomes from 25% to 200% increase of roadway capacity into our model.

### 4.1.4 Travel Demand

AVs that do not need human drivers or monitors may substantially increase mobility for those who cannot (legally) drive themselves because of youth, age, disability, or incapacitation (Fagnant and Kockelman, 2015) (Litman, 2015). However, poverty may be one of the most critical reasons that will prevent access to AVs for those potential users (Smith, 2012). If this is the case, the possible travel demand increase from that set of new travelers may be offset by the reality that they are not affluent enough to afford the new technology, which indicates that travel demand will stay the same. However, for those users who can afford CAV technology, automation could stimulate user travel needs (Gucwa, 2014) (Spieser et al., 2014), due to the reduction in perceived time costs and the increase in smoother and more comfortable trips (Cuddy et al., 2014).

While the introduction of SAVs will reduce the levels of private vehicle ownership, SAVs will also add more vehicle miles traveled (VMT) to the network (Fagnant and Kockelman, 2014, Speiser et al., 2014). According to the information introduced above, in the scenarios involving CAVs, the trip generation rates of households above the median income groups are increasing by 20%, 40%, 60%, 80%, and 100%, respectively, in different scenarios.

### 4.1.5 Mode Choice

*Value of Travel Time*

The most significant difference between conventional vehicles and fully AVs is that no driver is needed to complete the trip, which means drivers are set free to perform other activities, such as using cell phones, reading, watching movies, preparing work reports, and even sleeping. This significant change will absolutely overturn the long-established perception of travel time. Traveling with fully AVs would be considered a productive activity, resulting in decreased value of travel time (VOTT).

VOTT is a critical factor that will be incorporated into the generalized costs to combine travel time and financial costs. The VOTT has the function to change the units of travel time to dollars, which leads to the same units for the travel time and financial costs.

Petersen and Vovsha (2006) found that higher income households tend to drive newer vehicles, and among household members, the new vehicles are allocated to workers first, and then to retirees and under-18 drivers.

A similar trend might initially occur with AV adoption (Childress et al., 2014). To test AV technology impact on travel time, trip-based VOTTs were reduced by 65% for highest-income households in the traffic assignment step, and in the travel demand model, the automobile travel time was directly modified to be 65% of skimmed travel time in the skims for the high VOTT trips. Burns et al. (2013) conducted a case study of SAVs in Ann Arbor, Michigan, that indicates an SAV fleet can provide the same mobility as personally owned vehicles at far less cost by reducing parking costs and VOTT. The U.S. median income is $50,000 per year, which equates to $25/hour, yielding a VOT of $0.85 per mile. Combining the median time value of

\$0.85 per mile, with the out-of-pocket cost of \$0.75 per mile for a medium sedan driven the median annual distance of 10,000 miles, we arrive at a cost-plus-time value of \$1.60 per mile to use a personally owned vehicle. Using an SAV could reduce that traffic cost to\$0.15 per mile.

Kim et al. (2015) maintained that AVs will allow users to perceive travel time disutility, because in-vehicle travel time (IVTT) becomes less onerous and more productive, which will affect mode choice. In order to reflect this characteristic of AVs, in their Metro Atlanta activity-based model, Kim et al. decreased IVTT coefficients for autos by 50%, yielding a 71% reduction in vehicle operating costs as compared to the base model.

Gucwa (2014) handled the uncertainty about automated time-costs by considering four different IVTT coefficient values across a range of scenarios. In the base scenario, the VOTT wasn't changed. In the extreme scenario, the VOTT was assigned to zero. In the other two scenarios, the VOTT of AVs was equal to 30% lower than that of conventional cars and 60% lower than that of transit.

In order to value the convenience of fully AVs, we included the following question in the project survey of Texans: "How much money you are willing to pay (WTP) to save 15 minutes of travel time during a typical 30-minute ONE-WAY journey you make at least once a week (for example, home to work)?" In all, 1,364 Texans completed the response of this question.

The resulting answers indicated that Texans' average WTP to save 15 minutes of travel time on a 30-minute one-way trip is \$6.80, but this figure increases to \$9.50 if we remove those respondents with \$0 WTP for this benefit (28.5%). This result also indicates that most Texans associate significant monetary value with their travel time and are ready to pay more to travel faster. The VOTT is \$27.20, as derived from this question.

Based on the literature review results and our survey, we considered four AV VOTT scenarios in our model. In our base model, the VOTT stayed the same as the conventional vehicles. In the extreme scenario, the VOTT was set up to zero to maximize the benefits of AVs. In other two scenarios, VOTT was equal to the transit VOTT of transit and 50% of the VOTT of conventional vehicles.

*Parking Costs*

Parking cost was considered in the utility equation of mode choice. It is reasonable that decreasing parking cost can attract more trips to an area. One critical impact of AVs on traffic behavior is a change in parking patterns, as AVs can self-park in less expensive areas (Fagnant and Kockelman, 2015).

Childress et al. (2014) set parking costs to half the original level to reflect AVs self-parking in cheaper locations or better utilizing existing space. The change was made only in zonal parking costs and does not capture VMT generated from vehicles seeking more distant parking spaces or even roaming the streets waiting for pickup commands. Kim et al. (2015) further increase the AV parking benefits by setting the parking price to zero at the primary destination. A similar assumption was also made in the Levin's (2015) travel demand model, which allows AVs to avoid parking fees.

**Table 4.1: Parameters Set Up for Model Scenarios**

| Capacity improvement | Trip generation | VOT | Parking costs |
|---|---|---|---|
| 25%, 50%, 75%, 100%, 150% and 200% | Work-related stay the same, other trip purposes increased by 20%, 40%, 60%, 80%, and 100% | \$0, ¼ of autos, ½ of autos VOT and equal transit VOT | \$0 and ½ of current parking costs |

An SAV will essential function as a kind of autonomous taxi, which can operate by itself without human manipulation, other than input regarding a traveler's destination. Although SAVs will stimulate VMT due to empty vehicle relocation trips, they can provide significant environmental benefits, particularly in the form of reduced parking and vehicle ownership needs (Fagnant and Kockelman, 2014). Zhang et al. (2015) developed simulation model to test the change in parking needs created by an SAV system. Their results indicate a proper SAV fleet can reduce parking needs by 70% while still meeting travelers' needs. Therefore, in our study, when an SAV system (or autonomous taxi system) is investigated, the parking cost for this type of mode can be set at 30% of the current parking cost of automobiles. In all, based on the information we presented above, AV parking costs were set in our travel demand model to zero, one-half of the current price, and one-fourth of the current price. In addition, if SAVs are considered in the travel demand model, their parking fees are equal to zero.

### 4.1.6 Results from Static Traffic Assignment Simulations

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

*Description of Experiments*

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

Due to lack of value-of-time (VOT) distribution data per zone, the same distribution (shown in Table 4.2) was used for each zone, with VOTs ranging from 1.15 to 22 in units of dollars per hour. Values of time were uniformly chosen from a range based on scaling an income distribution, and the log-normal expression with mean $\mathbb{E}[\nu]$ and standard deviation $\sigma_\nu$ was used to determine the class distribution of demand, as suggested by Yang and Meng (2001) and Huang and Li (2007). As shown in Table 4.2, the chosen range accommodates most variation in the distribution. The demand data did not include trip purpose. Since the data are for the AM peak, all trips are assumed to be for home-based work travel. Price may have different effects on commercial travel or other types of personal trips. The inverse friction function $\phi(C) = \frac{1}{C}$ was used in trip distribution and mode choice. Parking costs were estimated at \$5.00 per day for all zones due to more specific data not being available. Although downtown parking fees are often much higher, for long-term planning travelers are assumed to have the option of cheaper annual parking passes. Fuel cost was set at \$3.00 per gallon. If the price of gasoline increases, there will be a shift of users from personal vehicle use to public transit. The opposite is true if the gas price were to decrease.

**Table 4.2: Value-of-Time Distribution**

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

On initial availability for public use, CAVs may have a high purchase cost because of the novelty of the technology. As production increases, the cost is expected to decrease so that CAVs become more affordable. The assumption was made that higher income travelers also have higher VOT, and that income affects affordability of CAVs.

### 4.1.7 Convergence of Static Traffic Assignment

Because of the multi-class formulation, the traffic assignment variational inequality (VI) does not necessarily have a unique or even existent equilibrium (Marcotte and Wynter, 2004), and therefore the commonly used Frank-Wolfe algorithm is not guaranteed to converge. However, empirical results of running Frank-Wolfe on the downtown Austin network suggest that it converges to an equilibrium. Figure 4.1 shows the convergence for the simulation case in which the eight highest VOT classes constituted 55% of the CAV demand use. Convergence is measured through the average excess cost—for example, the average difference between observed and shortest path travel costs. Similar convergence was observed for all scenarios in the gradual expanding availability of CAVs experiment. Since there was convergence, one can be sure that an equilibrium was reached and the results are worthwhile.

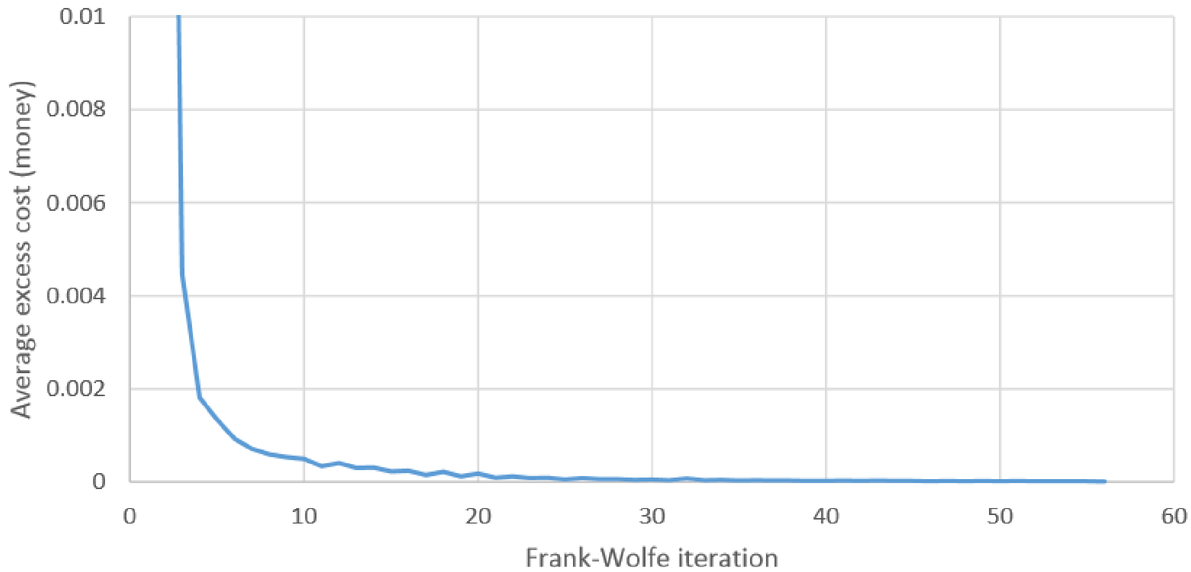



*Figure 4.1: Convergence of Traffic Assignment*

*Autonomous Vehicle Demand*

Figure 4.2 shows the decrease in transit demand as more VOT classes receive access to CAVs. Transit demand is high without CAVs because a high proportion of low VOT travelers, which are the majority of the demand choose transit. The pattern of decrease roughly follows the class proportions because the reduction in transit utility is primarily due to the lower cost of CAVs. When CAVs are available only to the upper classes, which comprise a small fraction of the population, the effect is small. However, as CAVs become available to lower-middle VOT classes, the rate of decrease in transit demand is much greater. Overall, the model predicts a reduction in transit ridership of 61% due to lower costs of CAVs for low VOT travelers (see Tables 4.3 and 4.4). CAV round-trip demand was a high fraction of the total personal vehicle demand, reaching 83% at full market penetration (Figure 4.3). This analysis also neglected the possible reduction in parking fees due to the economics of lower demand. However, because the alternative is a return trip, parking costs would likely need to be significantly lower to be competitive against the fuel cost of a return trip to the origin. Similarly, for transit to be competitive against CAVs, transit must provide benefits in cost or travel time. Transit costs in this model were $1, so a reduction in cost sufficient to be competitive against the lack of parking costs would be difficult. Despite the removal of the parking fee, CAVs still carry their own cost in relation to fuel consumption. However, restricted-access routes for transit such as bus rapid transit or metro could provide advantages in travel time.

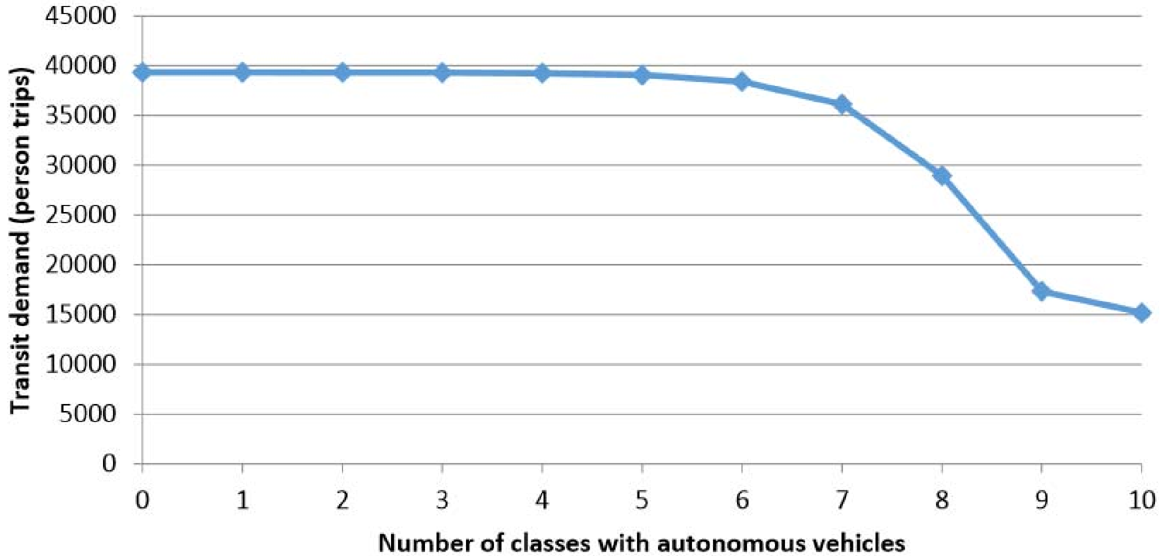



*Figure 4.2: Total Transit Demand*

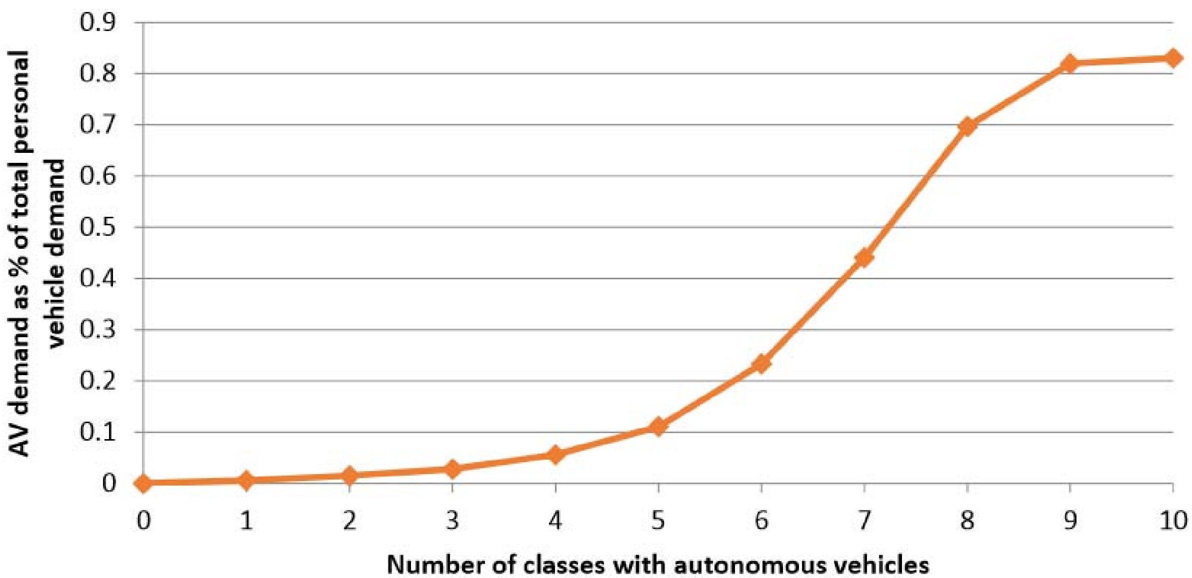



*Figure 4.3: CAV Round-Trip Demand as a Percentage of Total Personal Vehicle Demand*

*Long-term Effects*

Table 4.3 shows the mode split for each VOT class before any CAVs and after full CAV availability, and Table 4.4 shows the mode costs per class. The values shown in Table 4.4 are the costs associated with a single user's travel based on their mode choice. Total demand for any personal vehicle mode changed from 23,500 person trips to 47,676 trips, and with the shift to 39,592 CAV round-trips, the total number of trips made by personal vehicles increases to 87,275 an increase of 271%. Although many of these additional trips are traveling away from downtown, the network still experiences significant increases in link volume. However, average speed decreases are modest, as shown in Figure 4.4. This is encouraging because it suggests that the increases in demand are substantially offset by increases in capacity from CAVs.

**Table 4.3: Comparison of Mode-Specific Demand Before and After CAV Availability**

| User Class | Trip Distribution without CAVs | | | | Trip Distribution with CAVs | | |
|---|---|---|---|---|---|---|---|
| | Park | Transit | Round-Trip | | Park | Transit | Round-Trip |
| 1 | 3.1% | 96.9% | N/A for all Classes | | 1.4% | 49.0% | 49.6% |
| 2 | 15.2% | 84.8% | | | 6.1% | 33.0% | 60.9% |
| 3 | 41.4% | 58.6% | | | 15.1% | 19.6% | 65.4% |
| 4 | 64.1% | 35.9% | | | 20.9% | 12.0% | 67.1% |
| 5 | 78.9% | 21.1% | | | 24.3% | 7.8% | 67.8% |
| 6 | 88.0% | 12.0% | | | 26.6% | 5.3% | 68.1% |
| 7 | 92.3% | 7.7% | | | 27.8% | 3.9% | 68.2% |
| 8 | 95.5% | 4.5% | | | 28.9% | 2.8% | 58.3% |
| 9 | 97.3% | 2.7% | | | 29.6% | 2.1% | 68.3% |
| 10 | 98.2% | 1.8% | | | 30.0% | 1.7% | 68.2% |

**Table 4.4: Comparison of Mode and User-Class-Specific Costs (in $ [USD]) Before and After CAV Availability**

| User Class | Cost per User without CAVs | | | | Cost per User with CAVs | | |
|---|---|---|---|---|---|---|---|
| | Park | Transit | Round-Trip | | Park | Transit | Round-Trip |
| 1 | 5.9 | 2.0 | $2.7 | | 6.1 | 2.0 | 0.6 |
| 2 | 6.1 | 3.9 | 2.6 | | 6.3 | 3.8 | 0.8 |
| 3 | 6.2 | 5.7 | 2.6 | | 6.6 | 5.5 | 1.0 |
| 4 | 6.3 | 7.7 | 2.7 | | 6.9 | 7.3 | 1.2 |
| 5 | 6.5 | 9.6 | 2.7 | | 7.2 | 9.1 | 1.4 |
| 6 | 6.6 | 11.7 | 2.7 | | 7.6 | 11.1 | 1.7 |
| 7 | 6.8 | 13.4 | 2.7 | | 7.8 | 12.6 | 1.9 |
| 8 | 6.9 | 15.4 | 2.7 | | 8.2 | 14.6 | 2.1 |
| 9 | 7.0 | 17.5 | 2.7 | | 8.5 | 16.5 | 2.3 |
| 10 | 7.2 | 19.1 | 2.7 | | 8.7 | 18.0 | 2.5 |

*Effects on Traffic Congestion*

Figure 4.4 shows that average link travel speeds mirror the class proportions, indicating that the decrease in average link speeds is due to the switch to CAV round-trips. On the north/south bound freeways and arterials, much of the CAV round-trip traffic travels in the opposite direction away from workplaces in downtown. Within the downtown grid itself, CAV round-trips contribute to congestion while leaving the area. However, the changes are relatively small, suggesting that roadway capacity increases negate some of the additional vehicular travel demand. Average link speeds may be higher than expected because of the lack of intersection penalties, which are a major factor in the downtown region.

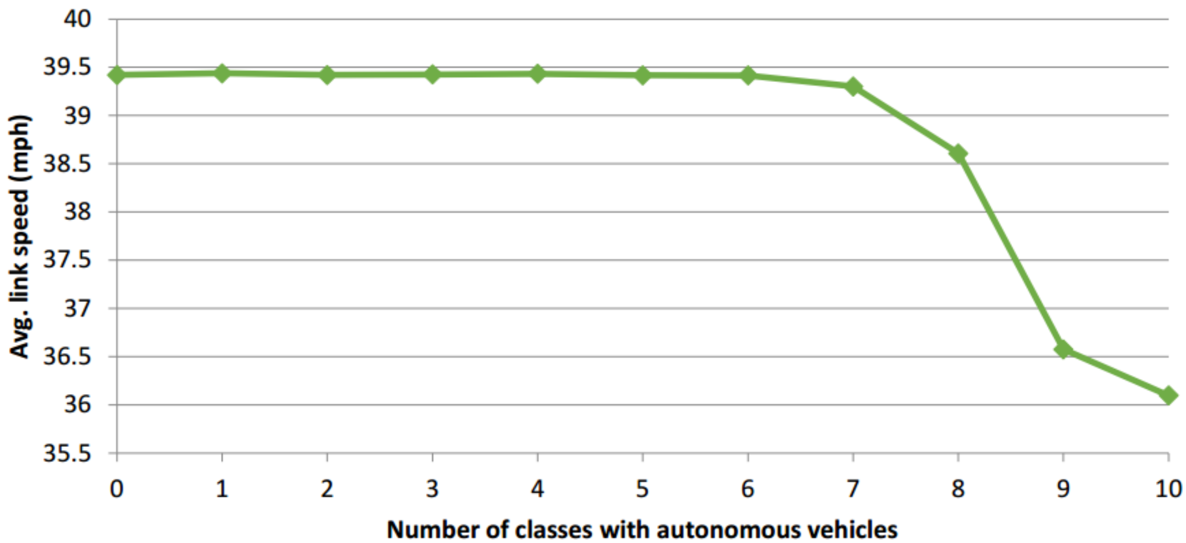



*Figure 4.4: Change in Average Link Speed, Weighted by Length, as CAV Availability Increases*

## 4.2 Link and node models

### 4.2.1 Multi-class Cell Transmission Model

This section presents a multi-class extension of the CTM developed for this project. The focus of this section is on roads with both HVs and personal AVs. In this model, the vehicles are differentiated by driver type but not by the physical performance characteristics. Therefore, we did not include the speed differences between vehicle classes, such as between heavy trucks and personal vehicles. The models in this section were defined for continuous flows, which some DTA models use. For these models, we made the following assumptions.

1. All vehicles travel at the same speed. Although in reality vehicle speeds differ, in DTA models the vehicle speed behavior model is often assumed to be identical for all vehicles. This is reasonable even with multiple vehicle classes because AVs may match the speed of surrounding vehicles even if it requires exceeding the speed limit. Although Tuerprasert & Aswakul (2010) consider different vehicle speeds in CTM, in this study of HVs and AVs most of the differences in speed would come from variations in HV behavior that are often not considered in DTA models.
2. Uniform distribution of class-specific density per cell. Single-class CTM assumes the density within a cell is uniformly distributed. We extend that assumption to class-specific densities.
3. Arbitrary number of vehicle classes. Although this task focuses on the transition from HVs to AVs, different types of AVs may be certified for different reaction times, and thus may respond differently in their car-following behavior.
4. Backwards wave speed is less than or equal to free-flow speed. This is necessary to determine cell length by free-flow speed.

We first define the multi-class hydrodynamic theory in Section 4.3.1.1. Then, following the presentation of Daganzo (1994), we state the cell transition equations in Section 4.3.1.2 and show that they are consistent with the multi-class hydrodynamic theory in Section 4.3.1.3.

*Multi-class Hydrodynamic Theory*

Let $M$ be the set of vehicle classes. Let $k_m(x,t)$ be the density of vehicles of class $m$ at space-time point $(x,t)$ with total density denoted by $k(x,t) = \sum m\epsilon M\ k_m(x,t)$. Similarly, let $u\left(\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}\right)$ denote the speed possible with class proportions of $\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}$, and let $q_m(x,t) = u\left(\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}\right)k_m(x,t)$ be the class-specific flow, with the total flow given by $q(x,t) = \sum_{m\in M} q_m(x,t)$.

Speed is limited by free-flow speed, capacity, and backwards wave propagation:

$$u(k_1,\ldots k_{|M|}) = min\left\{u^f,\frac{q^{max}\left(\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}\right)}{k},w\left(\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}\right)\left(k^{jam}-k\right)\right\} \tag{4.30}$$

where $u^f$ is free-flow speed, $w\left(\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}\right)$ is the backwards wave speed, $q^{max}\left(\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}\right)$ is the capacity when the proportions of density in each class are $\frac{k_1}{k},\ldots,\frac{k_{|M|}}{k}$, and $k^{\text{jam}}$ is jam density. $k^{\text{jam}}$ is assumed not to depend on vehicle type, as the physical characteristics (such as length and maximum acceleration) of HVs and AVs are assumed to be the same. For consistency, conservation of flow must be satisfied, i.e., $\frac{\partial q_m(x,t)}{\partial x} = \frac{\partial k_m(x,t)}{\partial t}$ for all $m \in M$ (2002).

*Cell Transition Flows*

As with Daganzo (1994), to form the multi-class CTM we discretize time into time steps of $dt$. Links are then discretized into cells labeled by $i = 1,,I$ such that vehicles traveling at free-flow speed will travel exactly the distance of one cell per time step. Let $n_i^m(t)$ be vehicles of class $m$ in cell $i$ at time $t$, where $n_i(t) = \sum_{m\in M} n_i^m(t)$. Let $y_i^m(t)$ be vehicles of class $m$ entering cell $i$ from cell $i-1$ at time $t$. Then cell occupancy is defined by

$$n_i^m(t+1) = n_i^m(t) + y_i^m(t) + y_{i+1}^m(t) \tag{4.31}$$

with total transition flows given by

$$y_i(t) = \sum_{m\in M} y_i^m(t) = \min\left\{\sum_{m\in M} n_{i-1}^m(t), Q_i(t), \frac{w_i(t)}{u^f}(N_i - \sum_{m\in M} n_i^m(t))\right\} \tag{4.32}$$

where $N_i$ is the maximum number of vehicles that can fit in cell $i$ and $Q_i(t)$ is the maximum flow.

Equation (4.32) defines the total transition flows, which will now be defined specific to vehicle class. To avoid dividing by zero, assume $n_{i-1}(t) > 0$. (If $n_{i-1}(t) = 0$, there is no flow to propagate). As stated in Assumption 2, class-specific density is assumed to be uniformly distributed throughout the cell. Then class-specific transition flows are proportional to $\frac{n_{i-1}^m(t)}{n_{i-1}(t)}$:

$$y_i^m(t) = \frac{n_{i-1}^m(t)}{n_{i-1}(t)}\min\left\{\sum_{m\in M} n_{i-1}^m(t), Q_i(t), \frac{w_i(t)}{u^f}(N - \sum_{m\in M} n_i^m(t))\right\} \tag{4.33}$$

Equation (4.33) may be simplified to

$$y_i^m(t) = \min\left\{n_{i-1}^m(t), \frac{n_{i-1}^m(t)}{n_{i-1}(t)} Q_i(t), \frac{n_{i-1}^m(t)}{n_{i-1}(t)} \frac{w_i(t)}{u^f}\left(N - \sum_{m\in M} n_i^m(t)\right)\right\} \tag{4.34}$$

which shows that flow of class $m$ is restricted by three factors: 1) class-specific cell occupancy; 2) proportional share of the capacity; and 3) proportional share of congested flow.

In the general hydrodynamic theory, class proportions may vary arbitrarily with space and time, which includes the possibility of variations within a cell. Therefore, assuming uniformly distributed density results in the possibility of non-FIFO behavior within cells. One class may have a higher proportion at the end of the cell, and thus might be expected to comprise a higher proportion of the transition flow. However, as discussed by Blumberg & Bar-Gera (2009), even single class CTMs may violate the principle of first-in-first-out (FIFO). The numerical experiments in this paper use discretized flow to admit reservation-based intersection models. The discretized flow also allows vehicles within a cell to be contained within a FIFO queue, which ensures FIFO behavior at the cell level. Total transition flows for discrete vehicles are determined as stated above for continuous flow.

*Consistency with Hydrodynamic Theory*

As with Daganzo (1994) we show that these transition flows are consistent with the multi-class hydrodynamic theory defined in Section 4.2.1.2.We assume class-specific flow is proportional to density (i.e., $\frac{k_m}{k}$) and that all classes travel at the same speed. Also assume that $k > 0$, because, if $k = 0$, then flow is also 0. Thus,

$$q_m(x,t) = \frac{k_m}{k} \min\left\{u^f k, q^{max}\left(\frac{k_1}{k}, \dots, \frac{k_{|M|}}{k}\right), wk\left(\frac{k_1}{k}, \dots, \frac{k_{|M|}}{k}\right)\left(k^{\text{jam}} - k\right)\right\} \tag{4.35}$$

Let $dt$ be the time step and choose cell length such that $u^f \cdot dt = 1$. Then, cell length is 1, $u^f$ is 1, $x = i$, $k^{\text{jam}} = N$, $q^{\max}(t) = Q(t)$, and $k(x,t) = n_i(t)$. Cell length is chosen so that flow may traverse at most one cell per time step to satisfy the Courant-Friedrichs-Lewy conditions (Courant et al., 1928). Therefore:

$$q_m(x,t) = \frac{n_i^m(t)}{n_i(t)} \min\left\{n_i(t), q_i^{\max}(t), \frac{w_i(t)}{v}\left(N - n_i(t)\right)\right\} = y_{i+1}^m(t) \tag{4.36}$$

except for the subindex of $n$ on the last term, which should be $i$+1 . As done in Daganzo (1994), this difference is disregarded. (See (1995) for more discussion on this issue.) Therefore $\frac{\partial q_m(x,t)}{\partial x} = y_{x+1}^m(t) - y_i^m(t)$. Since $\frac{\partial k_m(x,t)}{\partial t} = n_i^m(t+1) - n_i^m(t)$ is the rate of change in cell occupancy with respect to time, the conservation of flow equation $\frac{\partial q_m(x,t)}{\partial x} = \frac{\partial k_m(x,t)}{\partial t}$ is satisfied by the cell propagation function of equation (4.32).

*Link Capacity and Backwards Wave Speed*

We now present a car-following model based on kinematics to predict the speed-density relationship as a function of the reaction times of multiple vehicle classes. Car-following models can be divided into several types, as described by Brackstone et al. (1999) and Gartner et al. (2005). Some of these predict fluctuations in the acceleration behavior of an individual driver in response to the vehicle ahead. However, for DTA a simpler model is more appropriate to predict the speed of traffic at a macroscopic level. Newell (2002) greatly simplified car following to be consistent with the hydrodynamic theory, but the model does not include the effects of reaction time. Instead, the car-following model used here builds from the collision avoidance theory of Kometani & Sasaki (1961) to predict the allowed headway for a given speed, which varies with driver reaction time. The inverse relationship predicts speed as a function of the headway, which is determined by density. This car-following model results in the triangular fundamental diagram used by Newell (1993) and Yperman et al. (2005).

Although this car-following model is useful in predicting the effects of a heterogeneous vehicle composition on capacity and wave speed, other effects (such as roadway conditions) are not included. Furthermore, CTM assumes a trapezoidal fundamental diagram that enables a lower restriction on capacity. Therefore, the effect of reaction times on capacity and backwards wave speed are used to appropriately scale link characteristics for realistic city network models. Although AVs may be less affected by adverse roadway conditions than human drivers, this paper assumes similar effects for the purposes of developing a DTA model of shared roads. Other estimates of capacity and wave speed may also be included in the multi-class CTM model developed in Section 5.1.

*Safe Following Distance*

Suppose that vehicle 2 follows vehicle 1 at speed $u$ with vehicle lengths $\ell$. Vehicle 1 decelerates at $a$ to a full stop starting at time $t = 0$, and vehicle 2 follows suit after a reaction time of $\Delta t$. The safe following distance, $L$, is determined by kinematics.

The position of vehicle 1 is given by

$$x_1(t) = \begin{cases} ut - \frac{1}{2}at^2 & t \leq \frac{u}{a} \\ \frac{u^2}{2a} & t > \frac{u}{a} \end{cases} \tag{4.37}$$

where $\frac{u}{a}$ is the time required to reach a full stop. For $t > \frac{u}{a}$, the position of vehicle 1 is constant after its full stop. The position of vehicle 2, including the following distance of $L$, is

$$x_2(t) = \begin{cases} ut - L & t \leq \Delta t \\ ut - \frac{1}{2}a(t - \Delta t)^2 - L & t > \Delta t \end{cases} \tag{4.38}$$

The difference is

$$x_1(t) - x_2(t) = \begin{cases} u - \frac{1}{2}at^2 + L & t \leq \Delta t \\ -at\Delta t + \frac{1}{2}a(\Delta t)^2 + L & \Delta t < t \leq \frac{u}{a} \\ \frac{u^2}{2a} - ut + \frac{1}{2}a(t - \Delta t)^2 + L & t > \frac{u}{a} \end{cases} \tag{4.39}$$

and the minimum distance occurs when both vehicles are stopped, at $\frac{u}{a} + \Delta t$. To avoid a collision,

$$L \geq -\frac{u^2}{2a} + u\left(\frac{u}{a} + \Delta t\right) - \frac{1}{2}a\left(\frac{u}{a}\right)^2 + \ell = u\Delta t + \ell \tag{4.40}$$

*Flow-density Relationship*

Equivalently, equation (4.40) may be expressed as

$$u \leq \frac{L-\ell}{\Delta t} \tag{4.41}$$

which restricts speed based on following distance (from density). Flow may be determined from the relationship $q = \left(\frac{L-\ell}{\Delta t}\right) k$ with $L = \frac{1}{k}$, which is linear with respect to density. Figure 4.5 shows the resulting relationship between flow and density for different reaction times for a characteristic vehicle of length 20 ft (6.1 m) that decelerates at 9 $ft/s^2$ (2.7 $m/s^2$) for a free-flow speed of 60 mi/hr (96.6 km/hr). Since speed is bounded by free-flow speed and available following distance, the triangular fundamental diagram is described by $q = \min\left\{u^f k, \left(\frac{L-\ell}{\Delta t}\right) k\right\}$. Reaction times of 1 to 1.5 seconds correspond to human drivers (1971).

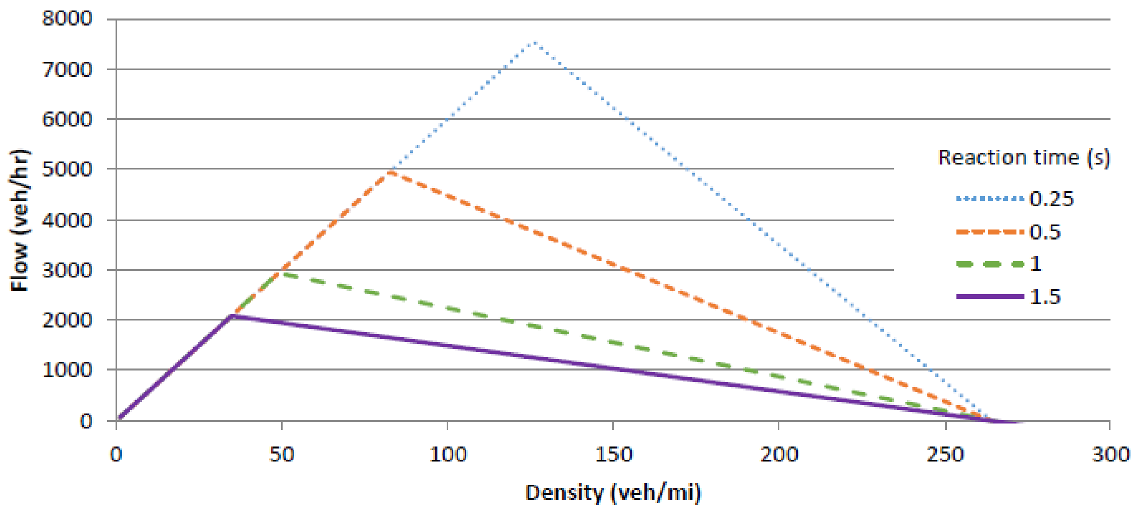



*Figure 4.5: Flow-density Relationship as a Function of Reaction Time*

The maximum density at which a speed of $u$ is possible is $\frac{1}{u\Delta t+\ell}$ from equation (4.41), so capacity under free-flow speed ( $u^f$) is

$$q^{\max} = u^f \frac{1}{u^f \Delta t+\ell} \tag{4.42}$$

And the backwards wave speed is:

$$w = -\frac{\frac{u^f}{u^f \Delta t+\ell}}{\frac{1}{u^f \Delta t+\ell}-\frac{1}{\ell}} = \frac{\ell}{\Delta t} \tag{4.43}$$

which increases as reaction time decreases. The direction of this relationship is consistent with micro-simulation results by Schakel et al. (2010). Note that if $\Delta t < \frac{\ell}{u^f}$, which may be possible for computer reaction times, then backwards wave speed exceeds free-flow speed. If $w > u^f$ for CTM, then the cell lengths would need to be derived from the backward wave speed, not the forward. That would complicate the cell transition flows. To avoid this issue, this paper assumes that $w \leq u^f$.

*Flow for Heterogeneous Vehicles*

The car-following model in the previous section is designed to estimate the capacity and backwards wave speed when the reaction time varies, but is uniform across all vehicles. This section expands the model for heterogeneous flow with different vehicles having different reaction times. Let the density be disaggregated into $k_m$ for each vehicle class $m$. Consider the case where speed is limited by density. Assuming that all vehicles travel at the same speed, for all vehicle classes,

$$u = \frac{L_m - \ell}{\Delta t_m} \tag{4.44}$$

where $L_m$ is the headway allotted and $\Delta t_m$ is the reaction time for vehicles of class $m$. Also, with appropriate units,

$$\sum_{m \in M} k_m L_m = 1 \tag{4.45}$$

is the total distance occupied by the vehicles. Thus

$$\sum_{m \in M} k_m (L_m - \ell) = 1 - k\ell \tag{4.46}$$

By equation (4.44),

$$\sum_{m \in M} k_m u \Delta t_m = 1 - k\ell \tag{4.47}$$

which results in

$$u = \frac{1 - k\ell}{\sum_{m \in M} k_m \Delta t_m} \tag{4.48}$$

Equation (4.47) may be rewritten as $u \sum_{m \in M} k_m \Delta t_m = 1 - k\ell$. Dividing both sides by $k$ yields

$$u \sum_{m \in M} \frac{k_m}{k} \Delta t_m + \ell = \frac{1}{k} \tag{4.49}$$

Assuming that vehicle class proportions $\frac{k_m}{k}$ remain constant because all vehicles travel at the same speed, the maximum density for which a speed of $u^f$ is possible is

$$k = \frac{1}{u^f \sum_{m \in M} \frac{k_m}{k} \Delta t_m + \ell} \tag{4.50}$$

which follows by taking the reciprocal of equation (4.49). Capacity is

$$q^{\max} = u^f \frac{1}{u^f \sum_{m \in M} \frac{k_m}{k} \Delta t_m + \ell} \tag{4.51}$$

Backwards wave speed is thus

$$w = -\frac{\frac{u^f}{u^f \sum_{m \in M} \frac{k_m}{k} \Delta t_m + \ell}}{\frac{1}{u^f \sum_{m \in M} \frac{k_m}{k} \Delta t_m + \ell} - \frac{1}{\ell}} = \frac{\ell}{\sum_{m \in M} \frac{k_m}{k} \Delta t_m} \tag{4.52}$$

Equations (4.48) through (4.52) reduce to the previous model in the single vehicle class scenario. Figure 4.6 shows an example of how capacity and wave speed increase as the AV proportion increases when human drivers have a reaction time of 1 second and AVs have a reaction time of 0.5 second. The cases of 0% AVs and 100% AVs are identical to the 1-second reaction time and 0.5-second reaction time fundamental diagrams in Figure 4.5, respectively.

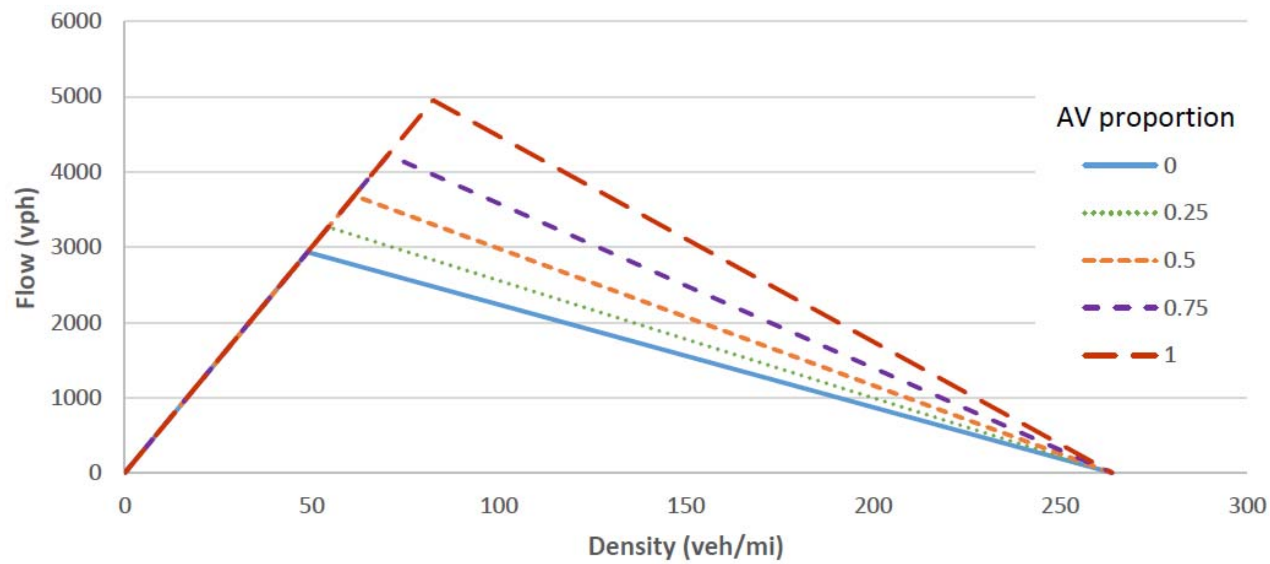



*Figure 4.6: Flow-density Relationship as a Function of AV Proportion.*

*Other Factors Affecting Capacity*

In reality, factors such as narrow lanes and road conditions affect capacity as well. These factors are usually in *Highway Capacity Manual* estimates of roadway capacity used for city network models. The model described above, however, does not include factors beyond speed limit. To include these factors, we scale existing estimates on capacity and wave speed in accordance with equations (4.51) and (4.52). Although the model in Section 17.2.3 predicts a triangular fundamental diagram, as used by Newell (1993) and Yperman et al. (2005), other flow-density relationships are often used. CTM, the basis for multi-class DTA in this paper, uses a trapezoidal fundamental diagram.

Here, estimates of roadway capacity and wave speed are $\hat{q}^{\max}$and $\hat{w}$, respectively, and the reaction time for human drivers is $\Delta t_{\mathrm{HV}}$. Human reaction times may vary depending on the location of the road; for instance, reaction times on rural roads are often longer than those in the city. Because capacity is affected by reaction time through equation (4.51), scaled capacity $\tilde{q}^{\max}$ is

$$\tilde{q}^{\max} = \frac{u^f \Delta t_{\mathrm{HV}} + \ell}{u^f \sum_{m \in M} \frac{k_m}{k} \Delta t_m + \ell} \hat{q}^{\max} \tag{4.53}$$

Similarly, wave speed is affected by reaction time through equation (4.52), so scaled wave speed $\widetilde{w}$ is

$$\widetilde{w} = \frac{\Delta t_{HV}}{\sum_{m \in M} \frac{k_m}{k} \Delta t_m} \widehat{w} \tag{4.54}$$

Equations (4.53) and (4.54) provide a method to integrate capacity and backwards wave speed scaling with other factors and realistic data.

*Summary*

Maturing AV technology suggests that AVs will be publicly available within the next few decades. To provide a framework for studying the effects of AVs on city networks, this section developed a shared road DTA model for human and autonomous vehicles. A multi-class CTM is presented for vehicles traveling at the same speed with capacity and backwards wave speed a function of class proportions. A collision avoidance car-following model incorporating vehicle reaction time is used to predict how reduced reaction times might increase capacity and backwards wave speed. These models are generalized to an arbitrary number of classes because different AVs may be certified for different reaction times. These models also use continuous flow so that SBDTA models built on continuous flows may incorporate these multi-class predictions.

### 4.2.2 Conflict Region Modeling

Tile-based reservation (TBR) intersection control for AVs has the potential to reduce intersection delays beyond optimized traffic signals. A major question in implementing reservations is the underdetermined problem of resolving conflicting reservation requests. Previous work studied prioritizing requests on a first-come-first-served (FCFS) basis or holding auctions at intersections, but there are many possibilities. Furthermore, although selfish routing behavior could affect the benefits of the reservation prioritization, reservation control has not been studied with user equilibrium routing due to its microsimulation definition. This report addresses these issues by presenting an integer program (IP) formulation of the conflict point simplification of reservations. The feasible region is transformed resulting in a more tractable IP on *conflict regions* for DTA. Because the IP may be NP-hard, we present a polynomial time heuristic. Finally, we demonstrate the potential utility of this heuristic by demonstrating objective functions that reduce congestion or energy consumption on a city network.

One major issue with TBR is the computational tractability of simulating vehicle movements through the grid of tiles. Smaller tiles result in greater intersection utilization but correspondingly greater computational requirements. TBR in its original form is therefore intractable for solving DTA. This issue has been addressed by two recent papers: Zhu and Ukkusuri (2015) and Levin and Boyles (2015). Zhu and Ukkusuri proposed a conflict point simplification, which focuses only on the intersections between turning movement paths in the grid of tiles. However, intersections with a large number of lanes and turning movements would have a correspondingly large number of conflict points, limiting the computational efficiency. Alternately, Levin and Boyles (2015) proposed to aggregate the tiles into larger *conflict regions* constrained by capacity. While effective for DTA, the justification for using conflict regions instead of tiles or conflict points was less clear. In addition, although the conflict region model admits an arbitrary priority function for resolving conflicts in reservation requests, the priority function does not directly correspond to an objective function for the intersection policy.

The work of Dresner and Stone (2004, 2006, 2005) on the TBR control used the advantages computers have over human drivers to improve utilization of intersection supply at the cost of greater complexity in vehicle-to-intersection communication and protocols. Experiments by Fajardo et al. (2011) on a variety of demand scenarios for a single intersection confirmed that TBR with the FCFS priority improves the level of service experienced by vehicles.

One major potential issue for TBR is that its communication complexity restricts usage by human drivers. Since it is likely that AVs will not be in exclusive use for many decades, extensions that allow humans to use reservation-based controls have been studied. Dresner and Stone (2006, 2007) proposed periodically providing a green light to specific lanes or links for human drivers. Qian et al. (2014) extended the reservation system to HVs and semi-AVs under certain assumptions about path and car-following behaviors, and Bento et al. (2013) proposed reserving larger sections of the intersection for HVs. Such interventions should be compatible with general

TBR strategies by requiring occasional allowances for non-AVs. Therefore, this paper focuses on the scenario in which all vehicles are autonomous.

Optimizing TBR is further complicated by the effects of UE routing, which can produce system inefficiencies such as the well-known Braess paradox (1968). Network studies of TBR have been complicated by its computational requirements. Previous network models by Carlino et al. (2012) and Vasirani and Ossowski (2012) have not included traffic assignment, and in some cases were forced to reduce the number of tiles for computational tractability at the cost of intersection efficiency. Zhu and Ukkusuri (2015) developed a linear program for flow through the conflict point model, albeit with some further restrictions on conflicting flow. Levin and Boyles (2015) developed the conflict region model of TBR for SBDTA, which was shown to be tractable for solving SBDTA on large city networks. For a more general model of reservation-based intersection control, we combine the conflict point and conflict region approaches by developing a discrete vehicle-based integer program (IP) for the conflict point model and transforming its feasible region to achieve the conflict region model.

*Derivation of the Conflict Region Model*

This section justifies the conflict region model by deriving it from the conflict point simplification of TBR control in three steps:

1. Section 4.2.2.2 presents an IP of the conflict point model *in microsimulation*. This IP models vehicles sequentially passing through conflict points while traversing their turning movements in continuous time. This section models vehicle movement similarly to the work on TBR.
2. In Section 4.2.2.3, we transform the conflict point IP for microsimulation to a conflict point IP for DTA. This involves replacing continuous time with discrete time steps. As is typical with SBDTA, vehicles crossing the intersection are assumed to begin and complete their turning movement within one time step. Therefore, in Section 4.2.2.3 we constrain conflict points by capacity rather than occupancy.
3. Section 4.2.2.4 presents the conflict region IP by aggregating conflict points into conflict regions. In Section 4.2.2.3, conflict points are constrained by capacity rather than occupancy for DTA. For computational tractability, we combine conflict points into larger conflict regions, which are also constrained by capacity.

*Conflict Point Model for Microsimulation*

The TBR control policy of Dresner and Stone (2004) operates on a grid of tiles in space-time. As noted by Zhu and Ukkusuri (2015), the tile conflict analysis of TBR may be simplified through the definition of conflict points. As illustrated in Figure 4.7, the paths for any two turning movements $(i, j)$ and $(i', j')$ first intersect at some point$c$. Ensuring adequate spacing at $c$ for vehicles traveling from $(i, j)$ and $(i', j')$ will guarantee that no conflict occurs at $c$ or anywhere in the intersection between vehicles moving from $i$ to $j$ and from $i'$ to $j'$. For vehicles uniform in physical characteristics and acceleration behaviors, these conflict points are fixed. However, in terms of practical implementation, tiles may be required instead of conflict points to handle vehicles of different shapes and turning behaviors. Nevertheless, in many DTA models physical uniformity of vehicles is assumed.

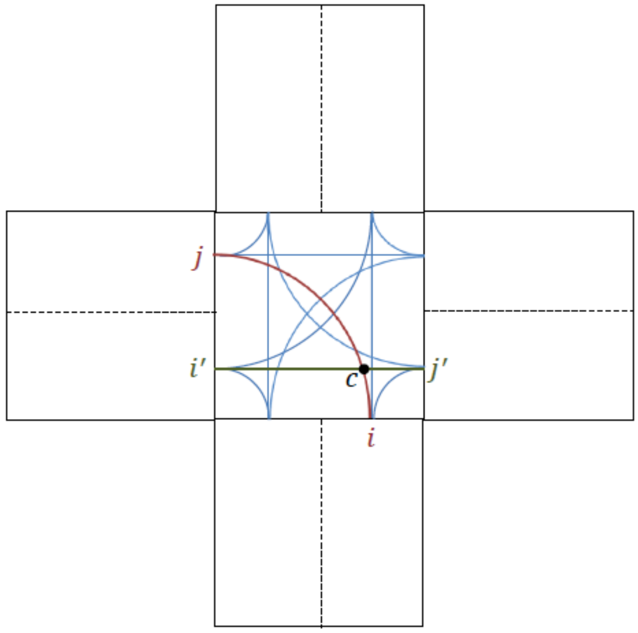



*Figure 4.7: Illustration of Intersections Between Turning Movement Paths.*

Previous work on TBR by Fajardo et al. (2011) studied tiles with width as small as 0.25 meters to improve intersection efficiency. Assuming 3-meter-wide lanes, the intersection in Figure 4.7 requires 676 such tiles in space. With 3 turning movements per link, and 4 links, there are a total of 12 paths through the intersection. In the worst case, in which each turning movement conflicts with all movements from other links, each turning movement has only 9 conflicts, for a total of 108 conflict points. In general, for a rectangular intersection with $n$ lanes along the width and $m$ lanes along the height, the number of tiles is $\Theta(nm)$. Assuming vehicles are not permitted to change lanes in the intersection, the number of turning movements is $O(n+m)$, and thus the number of conflict points is $O((n+m)^2)$. Therefore, the conflict point model may scale worse than the tile model. However, as demonstrated by the analysis of Figure 4.7, the conflict point model may be significantly more efficient for small intersections. The conflict point model also admits mathematical programming methods, as demonstrated by Zhu and Ukkusuri (2015).

Zhu and Ukkusuri (2015) assume that vehicles cannot simultaneously propagate through two conflicting lane movements. Depending on the magnitude of the time step, this may or may not be the most accurate assumption. For sufficiently large time steps allowing adequate spacing, two vehicles from conflicting turning movements should be able to traverse a single conflict point. This assumption is relaxed in the following IP formulation.

Let $C_{\text{P}}$ be the set of conflict points. For any *lanes* $i$ and $j$ denote by $\pi_{ij}$ the subset of $C_{\text{P}}$ that vehicles traveling from $i$ to $j$ will pass through. The conflict point model is built on lane-specific turning movements because the intersection points may differ depending on which lanes vehicles are traveling between. Assume for this conflict point model that all vehicles enter the intersection at the same speed so that the travel time between conflict point $c$ and the next point on path $\pi$ is denoted $\tau_\pi^c$. Although this is an unrealistic assumption for micro-simulation, it is sufficient for first-order SBDTA models (predicting speeds but not accelerations), which is the focus of this paper.

We present an original IP formulation for the conflict point model in microsimulation on a single intersection. In later sections it will be transformed to be used for a single DTA time step. Let $S$ be the set of vehicles wanting to cross the intersection and $S_i$ the subset of $S$ departing lane $i$. For any vehicle $v$, denote by $\gamma^{-1}(v)$ the incoming lane for $v$, let $\theta(v)$ be the time $v$ arrives at the intersection, let $\pi_v$ be the path traversed by $v$, and let $t_v(c)$ be the time $v$ crosses conflict point $c$. $t_v(c)$ are the decision variables for the intersection manager. We use $t$ to denote continuous time decision variables and $t$ for the discretized time in SBDTA. Let $\Gamma^{-1}$ and $\Gamma$ be the sets of incoming and outgoing lanes, respectively.

For any $c \in C_{\mathrm{P}}$, let $\Delta\tau_c(i)$ be the required separation for other vehicles after a vehicle from lane $i$ passes through $c$. The separation may depend on the directional orientation of the vehicle; a vehicle in the midst of a turn may cause greater separation requirements for following vehicles. Therefore, for any $v$, $v'$, $c$ with $c \in \pi_v$ and $c \in \pi_{v'}$, if $t_v(c) > t_{v'}(c)$ then $t_v(c) - t_{v'}(c) \geq \Delta\tau_c\big(\gamma^{-1}(v')\big)$. This is modeled by the ordering variable $\eta^c_{v,v'} \in \{0,1\}$ with $\eta^c_{v,v'} \leq 1 + \frac{t_v(c)-t_{v'}(c)}{M}$ and $\eta^c_{v,v'} \geq \frac{t_v(c)-t_{v'}(c)}{M}$, where $M$ is a large positive constant. These constraints result in $\eta^c_{v,v'} = 1$ if and only if $t_v(c) > t_{v'}(c)$. Then separation is ensured by the constraint $t_v(c) - t_{v'}(c) \geq \Delta\tau_c\big(\gamma^{-1}(v')\big)$. Note that if two vehicles conflict at multiple points, separation need only be checked at the first conflict. However, this formulation is presented for analytical, not computational, purposes as a more efficient model will be derived later.

The model below also assumes that flow into outgoing lanes is restricted only by a conflict point at the start of the lane. As this is unrealistic, in Section 18.1.2 this is replaced by a receiving flow constraint to be compatible with general SBDTA models. The intersection reservations may then be modeled as the following IP:

$$\max \quad Z(\boldsymbol{t}) \tag{4.55}$$

$$\text{s.t.} \quad t_v(c) = t_v(c-1) + \tau^{c-1}_{\pi_v} \qquad \forall v \in S, \forall c \in \pi_v \tag{4.56}$$

$$t_v(c) - t_{v'}(c) \geq \Delta\tau_c\big(\gamma^{-1}(v')\big) + M\eta^c_{v,v'} \qquad \forall v \in S, \forall c \in \pi_v, \forall v' \in S: c \in \pi_{v'} \tag{4.57}$$

$$\eta^c_{v,v'} \leq 1 + \frac{t_v(c)-t_{v'}(c)}{M} \qquad \forall v \in S, \forall c \in \pi_v, \forall v' \in S: c \in \pi_{v'} \tag{4.58}$$

$$\eta^c_{v,v'} \geq \frac{t_v(c)-t_{v'}(c)}{M} \qquad \forall v \in S, \forall c \in \pi_v, \forall v' \in S: c \in \pi_{v'} \tag{4.59}$$

$$\eta^c_{v,v'} \in \{0,1\} \qquad \forall v \in S, \forall c \in \pi_v, \forall v' \in S: c \in \pi_{v'} \tag{4.60}$$

$$\frac{t_v(0)-t_{v'}(0)}{\theta(v)-\theta(v')} \geq 0 \qquad \forall v \in S, \forall v' \in S_{\gamma^{-1}(v)} \tag{4.61}$$

$$t_v(c) \geq 0 \qquad \forall v \in S, \forall c \in \pi_v \tag{4.62}$$

where $t$ is the vector of $t_v(c)$ decision variables. Constraint (4.56) enforces travel time between conflict points, constraints (4.57) through (4.59) ensure separation, and constraint (4.61) enforces FIFO behavior for each lane: if $\theta(v) - \theta(v') > 0$, then $t_v(0) - t_{v'}(0) \geq 0$ as well in FIFO behavior. If, for all lanes $i$, and for all vehicles $v, v' \in S_i$, $\theta(v) = \theta(v') \Longrightarrow v = v'$ then $\theta(v) = \theta(v') \neq 0$ admitting the constraint (6.4). The objective function $Z$ is left unspecified for generality. Previous studies have considered FCFS policies, priority for emergency vehicles (2006), and intersection auctions (Schepperle et al. 2007 and 2008, Vasirani and Ossowski 2010, and Carlino et al. 2013). However, other strategies are worth consideration as well.

The above IP could potentially contain many variables because it is not restricted to a time interval, which could make it difficult to solve. We will now transform the feasible region to be solved within a single time step in SBDTA.

*Conflict Point Model for DTA*

This section transforms the IP formulated in Section 4.2.2.2 to be solved for individual time steps in SBDTA models. Let $x_v(t)$ denote whether vehicle $v$ enters the intersection in time step $t$. $S(t)$, the set of vehicles that are waiting to enter the intersection in time step $t$, is the sending flow in time $t$. We assume that $S(t)$ includes vehicle order. $S_i(t)$ is the sending flow disaggregated by lane.

In most SBDTA models, vehicles are assumed to begin and complete turning movements within the same time step. Turning movements spanning multiple time steps are normally not considered. However, constraint (4.56) of conflict point arrival times could violate this assumption because vehicles entering the intersection late in one time step would not be able to complete their turning movement within the same time step. Therefore, instead of constraining the arrival times of individual vehicles at conflict points, we constrain the total flow through each conflict point during each time step. This is equivalent to a major difference between micro-simulation and DTA: in car-following models, vehicles decelerate to avoid colliding with the vehicle in front; in DTA, speed decreases as density increases to model vehicle deceleration to avoid collisions.

Constraints (4.57) through (4.60) on conflict point arrival spacing are not meaningful without constraint (4.56). Therefore, we transform conflict point spacing to a capacity-based restriction. Although this reduces the power of the model to prevent intersection conflicts, conflicting movements still constrain flow at an aggregate level consistent with SBDTA flow models. Let $\delta_v^c$ denote whether $c \in \pi_v$, and let $Q_c$ be the capacity of conflict region $c$. Vehicles from $\gamma^{-1}(v)$ require a spacing headway of $\Delta\tau_c(\gamma^{-1}(v'))$ where $Q_c(i)$ is the capacity for vehicles from lane $i$ moving through $c$. Then the separation constraint becomes $\sum_{v\in S(t)} x_v(t)\delta_v^c \frac{1}{Q_c(\gamma^{-1}(v))} \leq \Delta t$, where $\Delta t$ is the simulation time step. This may be written as $\sum_{v\in S(t)} x_v(t)\delta_v^c \frac{Q_c}{Q_c(\gamma^{-1}(v))} \leq Q_c\Delta t$, which yields the capacity reduction in Levin and Boyles (2015). In addition, we add a receiving flow constraint for all lanes $j$: $\sum_{v\in S(t)} x_v(t)\delta_v^j \leq R_j(t)$, where $\delta_v^j$ denotes whether $v$ enters lane $j$.

The FIFO constraint must also be transformed because SBDTA may not assign each vehicle a unique arrival time at the intersection. However, assume that SBDTA determines arrival order for discrete vehicles. Let $\tilde{S}_v(t) = \{v' \in S_{\gamma^{-1}(v)}(t): \theta(v) > \theta(v')\}$ be the set of vehicles that arrived at the intersection before $v$. Then all $v' \in \tilde{S}_v(t)$ must move before $v$ due to FIFO, which may be written as $x_v(t) \leq 1 - \frac{|\tilde{S}_v(t)| - \sum_{v'\in\tilde{S}_v(t)} x_{v'}(t)}{M}$. If $\left|\tilde{S}_{\gamma^{-1}(v)}(t)\right| - \sum_{v'\in\tilde{S}_v(t)} x_{v'}(t) > 0$ then at least one vehicle in front of $v$ has not yet moved, and the lane is blocked for $v$.

The result of these transformations is the following IP. Note that this program is for every time step $t$, so $t$ is assumed fixed.

$$\text{Max} \quad Z(\mathbf{x}(t)) \tag{4.63}$$

$$\text{s.t.} \quad \sum_{v\in S(t)} x_v(t)\delta_v^c \frac{1}{Q_c(\gamma^{-1}(v))} \leq \Delta t \qquad \forall c \in C_{\text{P}} \tag{4.64}$$

$$\sum_{v \in S(t)} x_v(t) \delta_v^j \leq R_j(t) \qquad \forall j \in \Gamma \tag{4.65}$$

$$x_v(t) \leq 1 - \frac{|\tilde{S}_v(t)| - \sum_{v' \in \tilde{S}_v(t)} x_{v'}(t)}{M} \qquad \forall c \in C_{\mathrm{P}} \tag{4.66}$$

$$x_v(t) \in \{0,1\} \qquad \forall v \in S(t) \tag{4.67}$$

where $\mathrm{x}(t)$ is the vector formed by the decision variables $x_v(t)$.

*Conflict Region Model*

With the relaxation of the constraint on arrival time sequencing to capacity, conflict points may be combined in the model for computational efficiency. This could result in a capacity reduction due to modeling a conflict between two turning movements that do not intersect, but if all points in a sufficiently large conflict region are combined it is likely that the paths would have intersected at one of those points. With the aggregation of conflict points into conflict regions, denoted by the set $C_{\mathrm{R}}$, lanes may similarly be aggregated into links. Thus, from this point forward, $\gamma^{-1}(\mathrm{v})$ and $\gamma(\mathrm{v})$ refer to the incoming and outgoing *links* for vehicle $v$, respectively. Denote by $\ell_i$ the number of lanes link $i$ has. The number of lanes affects the FIFO constraint because vehicles cannot enter the intersection unless they are at the front of a lane. This results in the following IP:

$$\text{Max} \quad Z(\mathbf{x}(t)) \tag{4.68}$$

$$\text{s.t.} \quad \sum_{v \in S(t)} x_v(t) \delta_v^c \frac{Q_c}{Q_c(\gamma^{-1}(v))} \leq Q_c \Delta t \qquad \forall c \in C_{\mathrm{P}} \tag{4.69}$$

$$x_v(t) \leq 1 + \frac{\tilde{Q}_{\gamma^{-1}(v)} - 1}{M} \qquad \forall v \in S(t) \tag{4.70}$$

$$\sum_{v \in S(t)} x_v(t) \delta_v^j \leq R_j(t) \qquad \forall j \in \Gamma \tag{4.71}$$

$$x_v(t) \in \{0,1\} \qquad \forall v \in S(t) \tag{4.72}$$

where

$$\tilde{Q}_{\gamma^{-1}(v)}(v) = \left(Q_i - \sum_{v \in \tilde{S}_v(t)} x_v(t)\right)\left(\frac{\ell_{\gamma^{-1}(v)} - \left(|\tilde{S}_v(t)| - \sum_{v' \in \tilde{S}_v(t)} x_{v'}(t)\right)}{\ell_{\gamma^{-1}(v)}}\right) \tag{4.73}$$

Constraints (4.70) and (4.73) are the generalization of constraint (4.51) for multiple lanes. When a vehicle blocks a lane due to a rejected reservation, the capacity for vehicles behind is restricted. This is modeled by the function $\tilde{Q}_{\gamma^{-1}(v)}(v)$, which is the remaining capacity for $v$ as a function of whether vehicles ahead of $v$ moved through the intersection. The number of lanes available for use for $v$ is $\ell_{\gamma^{-1}(v)} - \left(|\tilde{S}_v(t)| - \sum_{v' \in \tilde{S}_v(t)} x_{v'}(t)\right)$. $Q_i - \sum_{v \in \tilde{S}_v(t)} x_v(t)$ is the remaining capacity of the link, which is reduced proportionally by the number of available lanes remaining. When $\tilde{Q}_{\gamma^{-1}(v)}(v) \geq 1$, then $x_v(t) = 1$ satisfies constraint (4.70). Note that $\tilde{Q}_{\gamma^{-1}(v)}(v) < 0$ is possible in a sufficiently large queue. If $\ell_{\gamma^{-1}(v)}$ or more vehicles in front of $v$ have not moved, then $\tilde{Q}_{\gamma^{-1}(v)}(v) \leq 0$, and $v$ cannot enter the intersection. Nevertheless, this IP always has a feasible solution:

**Proposition 1.** *Let $\mathcal{X}(t)$ be the set of feasible solutions to the conflict region IP. Then $\mathcal{X}(t) \neq \emptyset$.*

*Proof.* Consider $\mathrm{x}(t) = 0$. $R_j(t) \geq 0$ and $Q_c \Delta t \geq 0$ , so constraints (4.72) and (4.73) are satisfied. $1 + \frac{\tilde{Q}_{\gamma^{-1}(v)} - 1}{M} \geq 0$ so constraint (18.70) is satisfied. Therefore $0 \in \mathcal{X}(t)$.

*Satisfaction of Requirements for DTA Intersection Models*

As an intersection model for DTA, it is relevant to study the conflict region IP in equations (18.14) through (18.18) in the context of the requirements for generic DTA intersection models described by Tampère et al. (2011): 1) general applicability; 2) maximizing flows; 3) non-negativity; 4) conservation of vehicles; 5) satisfying demand and supply constraints; and 6) obeying conservation of turning fractions. As stated, the conflict region IP satisfies all requirements except the invariance principle. We show that the algorithm of Levin and Boyles (2015), which satisfies the invariance principle, creates a feasible solution for the IP.

General applicability is challenging for the many possibilities of intersection geometries. However, Levin and Boyles (2015) proposed a radial division of the intersection into conflict regions, which specifies the set $C_{\mathrm{R}}$ and the indicator variables $\delta_v^c$ for all $v \in S$, $c \in C_{\mathrm{R}}$. That radial division may be used for this IP.

For general applicability, we assume, as with Levin and Boyles (2015), that in the absence of other flow, flow between any $(i,j) \in \Gamma^{-1} \times \Gamma$ is constrained only by sending and receiving flows. Let $Q_i$ be the capacity of link $i$; if $Q_i = Q_j$, then flow of $Q_i$ should saturate the conflict region. This can be satisfied by choosing $Q_c = \max_{(i,j) \in \Gamma^{-1} \times \Gamma : c \in \pi_{ij}} \{\min\{Q_i, Q_j\}\}$, where $\pi_{ij}$ is the set of conflict regions flow from $i$ to $j$ will pass through. With $Q_c(\gamma^{-1}(v)) = Q_i$, then flow of $Q_i \Delta t$ through any conflict region $c$ will result in equality on constraint (6.15) because $\frac{Q_c}{Q_i} Q_i \Delta t = Q_c \Delta t$. Constraint (18.69) can then be written as

$$\sum_{v \in S(t)} x_v(t) \delta_v^c \frac{Q_c}{Q_{\gamma^{-1}(v)}} \leq Q_c \Delta t \qquad \forall c \in C_{\mathrm{R}} \tag{4.74}$$

Tampère et al. (2011) note that DTA intersection models should maximize flow as drivers will move whenever possible. In a reservation-based context, vehicles may be prevented from moving even if it is possible for them to move. However, it is reasonable to assume that many practical intersection strategies will allow a vehicle to move if its reservation request does not conflict with the reservation of another vehicle and the downstream link has sufficient space. To achieve this, the objective function in (18.14) should satisfy the following:

**Property 1.** *For any $x(t) \in \mathcal{X}(t)$, if for all $v \in S(t)$ $x'_v(t) \geq x_v(t)$ and there exists a $v \in S(t)$ with $x'_v(t) > x_v(t)$, then $Z(\mathrm{x}(t)) < Z(\mathrm{x}'(t))$.*

Objective functions satisfying Property 1 yield the desired characteristic of the solution to the conflict region IP:

**Proposition 2.** *Let $\mathrm{x}^*(t)$ be an optimal solution to the conflict region IP and let $Z(\cdot)$ satisfy Property 1. For any $v \in S(t)$, if $x_v^*(t) = 0$, form $\mathrm{x}'(t)$ with $\mathrm{x}'(t) = \mathrm{x}^*(t)$ except with $x_v^*(t) = 1$. Then $\mathrm{x}'(t)$ is not feasible.*

*Proof.* Suppose $\mathrm{x}'(t)$ is feasible. Since $Z(\cdot)$ satisfies Property 1, then $Z(\mathrm{x}'(t)) < Z(\mathrm{x}^*(t))$, which contradicts $\mathrm{x}^*(t)$ being optimal.

Property 1 can be satisfied by $Z(\mathbf{x}(t)) = \mathbf{z} \cdot \mathbf{x}(t)$ for some $\mathbf{z} > \mathbf{0}$ or more complex functions. It does not, however, require that the objective is to maximize flow. For instance, FCFS can be modeled through the conflict region IP.

**Proposition 3.** *The FCFS policy may be modeled through the IP in equations (4.68) through (4.69). Specifically, there exists an objective function $Z(\cdot)$ satisfying the following: Let $\hat{\theta}(v)$ be the reservation time of $v$. If, for all $v_1, v_2 \in S(t)$, $v_1 \neq v_2 \Longrightarrow \hat{\theta}(v_1) \neq \hat{\theta}(v_2)$ and $\mathrm{x}^*(t)$ is chosen by FCFS, then for all $\mathrm{x} \in \mathcal{X}$, $Z(\mathrm{x}(t)) < Z(\mathrm{x}^*(t))$.*

*Proof.* By induction on $|S(t)|$. Sort $S(t)$ by reservation request so that for any indices $i, j$, if $i < j$ then $\hat{\theta}(v_i) < \hat{\theta}(v_j)$. Let $t^*$ be the reservation time of the last vehicle, and let

$$Z(\mathrm{x}(t)) = \sum_{i=1}^{n} M^{t^*-\hat{\theta}(v_i)} x_{v_i}(t) \tag{4.75}$$

be the objective function. (This satisfies Property 1). We show that $\sum_{i=1}^{n} M^{t^*-\hat{\theta}(v_i)}\, x^*_{v_i}(t) \geq \sum_{i=1}^{n} M^{t^*-\hat{\theta}(v_i)}\, x_{v_i}(t)$ for all $\mathrm{x}(t) \in \mathcal{X}(t)$, for all $1 \leq n \leq |S|$.

*Base case:* If $v_1$ can move, then $\sum_{i=1}^{1} M^{t^*-\hat{\theta}(v_i)}\, x^*_{v_i}(t) = M^{t^*-\hat{\theta}(v_1)}$ because FCFS prioritizes by request time, and $M^{t^*-\hat{\theta}(v_1)} \geq \sum_{i=1}^{1} M^{t^*-\hat{\theta}(v_i)}\, x^*_{v_i}(t)$ for all $\mathrm{x}(t)$. If $v_1$ is blocked, then $\sum_{i=1}^{1} M^{t^*-\hat{\theta}(v_i)}\, x^*_{v_i}(t) = 0$ for all $\mathrm{x}(t)$.

*Inductive step:* If $x^*_{v_{n+1}} = 1$ or $x^*_{v_i} = 0$ for all $1 \leq i \leq n+1$, then this holds trivially. The remaining case is that $x^*_{v_{n+1}} = 0$ because of higher priority vehicle(s) blocking its movement, i.e., if $x_{v_{n+1}} = 1$ then for some vehicle $i < n+1$, $x_{v_i} = 0$. Because $M^{t^*-\hat{\theta}(v_i)} > \sum_{v \in S_{\gamma^{-1}(v)}, t_v > t_{v_i}} M^{t^*-\hat{\theta}(v)}$, $\sum_{j=i}^{n+1} M^{t^*-\hat{\theta}(v_j)}\, x^*_{v_j} > \sum_{j=i}^{n+1} M^{t^*-\hat{\theta}(v_j)}\, x^*_{v_j}$. Then by the inductive hypothesis, $\sum_{j=i}^{n+1} M^{t^*-\hat{\theta}(v_j)}\, x^*_{v_j} > \sum_{j=i}^{n} M^{t^*-\hat{\theta}(v_j)}\, x^*_{v_j}$.

Proposition 3 proves that the oft-studied FCFS policy falls within the general framework of the IP developed here. Setting $M = \Delta t$ should be sufficiently large, although that may still result in impractically large numbers due to the exponential. We prove in Proposition 6 that the polynomial-time algorithm of Levin and Boyles (2015) can solve the IP with objective (4.75).

Tampère et al. (2011)'s requirement of non-negativity is satisfied because $\mathrm{x}(t) \geq 0$. Tracking discrete vehicles also satisfies conservation of flow and of turning fractions. Demand constraints are satisfied by the implicit definition of the set of sending flow, and supply constraints are explicitly satisfied by equation (4.61).

The remaining requirement is the invariance principle, which essentially states that the intersection flow should be invariant to the constraint on sending flow changing from the number of waiting vehicles to the link capacity. The invariance principle may not be satisfied for general objective functions, although it is for some objectives, including FCFS (1971). If $|S_i(t)| < Q_i$ changes to $|S'_i(t)| = Q_i$, if one $v \in S'_i - S_i$ has a very high weight in the objective function, the optimal solution to the conflict region IP may need to include $v$. The invariance principle can be satisfied by an additional constraint (2010), or as a corollary of alternate solution algorithms. For instance, the conflict region algorithm of Levin and Boyles (1971) satisfies the invariance principle. With a small change to better model FIFO constraints, shown in Algorithm [alg1], the conflict region algorithm finds a feasible solution to the conflict region IP. Specifically, $\tilde{\ell}_i$ tracks the number of lanes blocked. These are combined in line 20 to satisfy constraint (4.73).

**Proposition 4.** *The conflict region algorithm (Algorithm 1) produces a feasible solution to the conflict region IP in equations (4.68) through (4.72).*

*Proof.* For any $v \in S(t)$, let $V'$ be the set of vehicles considered before $v$ in the loop on line 7. If $x_v = 1$, then $v$ can move from $i$ to $j$ according to line 8. Line 9 results in $h_{i'j'}$ being the number of vehicles in $v'$ moving from $i'$ to $j'$. This results in line 19 requiring that $R_j \geq 1 + \sum_{v' \in V'} \delta_{v'}^{j} x_{v'}(t)$, so constraint (6.17) is satisfied. For all conflict regions $c$ that $v$ passes through, line 21 requires that $Q_c \geq \frac{Q_c}{Q_i} + \sum_{v' \in V'} \delta_{v'}^{j} x_{v'} \frac{Q_c}{Q_{\gamma^{-1}(v')}}$, satisfying constraint (18.15). Constraints (18.16) and (18.19)—FIFO—are satisfied because vehicles either move through the intersection or block a lane (line 17). Blocked lanes detract from outflow (line 19) and vehicles are considered for movement in FIFO order. Finally, constraint (18.18) is satisfied because each vehicle is only considered once in the loop on line 6.

**Algorithm 1** Conflict region algorithm

1: Set $V = \emptyset$
2: **for** all $i \in \Gamma^{-1}$ **do**
3:     Sort $S_i(t)$ by arrival time at $i$
4:     Remove first $\ell_i$ vehicles in $S_i(t)$ and add them to $V$
5:     Set $\tilde{l}_i = 0$
6:     **for** all $j \in \Gamma$ **do**
7:         Set $y_{ij}(t) = 0$
8:     **end for**
9: **end for**
10: Sort $V$ by $f(v)$
11: **for** all $v \in V$ **do**
12:     Let $(i, j)$ be the turning movement of $v$
13:     **if** *canMove*$(i, j)$ **then**
14:         Set $y_{ij}(t) = y_{ij}(t) + 1$
15:         **for** all $c \in C_{ij}$ **do**
16:             Set $y_c(t) = y_c(t) + \frac{Q_c}{Q_i}$
17:         **end for**
18:         Remove first vehicle in $S_i(t)$ and add it to $V$ in sorted order
19:         Set $x_v(t) = 1$
20:     **else**
21:         Set $x_v(t) = 0$
22:         Set $\tilde{l}_i = \tilde{l}_i + 1$
23:     **end if**
24: **end for**
25:
26: **function** *canMove*$\left(i \in \Gamma^{-1}, j \in \Gamma\right)$
27:     **if** $R_j - \sum_{i' \in \Gamma^{-1}} y_{i'j} < 1$ **or** $\left(Q_i - \sum_{j' \in \Gamma} y_{ij'}\right) \frac{\ell_i - \tilde{\ell}_i}{\ell_i} < 1$ **then**
28:         *Return False*
29:     **end if**

30: **for** all $c \in C_{ij}$ **do**
31: **if** $(Q_c - y_c(t) < \frac{Q_c}{Q_i}$ **then**
32: *Return False*
33: **end if**
34: **end for**
35: *Return True*
36: **end function**

---

**Proposition 5.** *The running time of the conflict region algorithm is* $O(|S(t)|\log|S(t)||C_{\mathrm{R}}| + |\Gamma^{-1}||\Gamma|)$.

*Proof.* Initialization of $V$ (lines 1 through 9) iterates through each vehicle in $S(t)$. Sorting $V$ (line 10) is therefore $O(|S(t)|\log|S(t)|)$. Initializing $y_i j(t)$ requires $O(|\Gamma^{-1}||\Gamma|)$. Therefore initialization is $O(|S(t)|\log|S(t)| + |\Gamma^{-1}||\Gamma|)$.

The main loop (lines 11 through 24) iterates through each vehicle at most once, scaling with $|S(t)|$. It may add vehicles to $V$ in sorted order, requiring $O(\log|S(t)|)$ time to find the appropriate index. For each vehicle, the destination link and the conflict regions it passes through is checked once for conflicts in the *canMove()* subroutine, which is $O(|C_{\mathrm{R}}|)$.If *canMove()* returns true, the flow through each conflict region is updated, also requiring $O(|C_{\mathrm{R}}|)$. Therefore, the main loop is $O(|S(t)|\log|S(t)||C_{\mathrm{R}}|)$.

Although the conflict region algorithm produces a feasible solution in polynomial time, it may not be optimal. It takes as input some priority $f(\cdot)$ to each vehicle, and moves the highest priority vehicle able to enter the intersection. It does not consider the value of moving a vehicle to allow vehicles behind to cross the intersection sooner. However, for specific objective functions, such as FCFS, the priority function will result in an optimal solution to the IP.

**Proposition 6.** *The conflict region algorithm, using reservation time as the prioritization ($f(v) = \hat{\theta}(v)$), produces an optimal solution for the FCFS policy.*

*Proof.* From Proposition 4, the solution created by the conflict region algorithm is feasible. Since vehicles cannot request a reservation unless they are not blocked from entering the intersection, for any two vehicles $v_1, v_2 \in S(t)$, $\theta(v_1) < \theta(v_2) \Longrightarrow f(v_1) \leq f(v_2)$. Therefore, if $v_1 \in V$ and $v_2 \notin V$, then $f(v_1) \leq f(v_2)$. Once at the front of the intersection, reservations are ordered by $f(\cdot)$ for consideration. Therefore, if the reservation of $v_1$ is rejected, there must be some $v_2$ with $f(v_2) \leq f(v_1)$ blocking the movement of $v_1$, which is the definition of FCFS.

*Division of Intersection into Conflict Regions*

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

We propose a *radial division* into conflict regions at incoming and outgoing links, as shown in Figure 4.8. This division does not require lane-specific turning movements but limits supply of specific areas of the intersection. This division can also be determined geometrically when link angles are known by the method below. Link angles can be determined through node coordinates, which are readily available from internet-based geographic information systems.

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

$$\mathbf{s}_i = \left(\cos(\phi_i + \pi), \sin(\phi_i + \pi)\right) + \epsilon\left(\cos\left(\phi_i - \frac{\pi}{2}\right), \sin\left(\phi_i - \frac{\pi}{2}\right)\right) \tag{4.76}$$

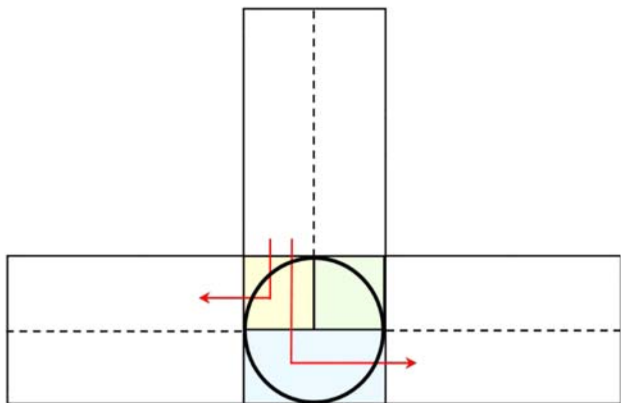


*Figure 4.8: Illustration of Radial Division on a Three-Approach Intersection*

The inner circle is divided by radii to the incoming and outgoing links.

$$\mathbf{s}_i = \left(\cos(\phi_i), \sin(\phi_i)\right) + \epsilon\left(\cos\left(\phi_i - \frac{\pi}{2}\right), \sin\left(\phi_i - \frac{\pi}{2}\right)\right) \tag{4.77}$$

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

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

All conflict regions crossed by the turning movement path (determined through angles to the center of the circle) are added to $(C_{\mathrm{R}})_{ij}$ , the set of conflict regions used by vehicles traveling from $i$ to $j$. Choose $\zeta_i^*$ and $\zeta_j^*$ such that $\boldsymbol{l}_i(\zeta_i^*) = \boldsymbol{l}_j(\zeta_j^*)$. Then

$$(C_{\mathrm{R}})_{ij} = \left\{\mathcal{r}\left(\tan^{-1}\left(\frac{s_2}{s_1}\right)\right) \middle| (s_1, s_2) \in \{\boldsymbol{l}_i(\zeta) | 0 \le \zeta \le \zeta_i^*\} \cup \{\boldsymbol{l}_j(\zeta) | 0 \le \zeta \le \zeta_j^*\}\right\} \tag{4.78}$$

Although this path may not model the curves traced by real vehicles, such curves are unnecessary for this division because conflict regions are not lane-specific. Figure 4.8 demonstrates this method applied to a typical three-approach intersection.

*Summary*

This section developed and optimized a simplification of the TBR described by Dresner and Stone (2004) for autonomous vehicles. We first formulated an IP for the conflict point transformation of TBR proposed by Zhu and Ukkusuri (2015). After transforming the IP for use in SBDTA, the spacing constraints were found to naturally reduce to capacity limitations on each conflict point. For computational tractability on large networks, we aggregated conflict points into conflict regions, resulting in a model similar to that of Levin and Boyles (2015) formulated as an IP. This admits arbitrary objective functions and can therefore be used to optimize the order that vehicles cross the intersection for a more general class of policies. Since IPs in general are NP-hard, we derived theoretical results about the conflict region algorithm of Levin and Boyles (2015). It solves the IP for the FCFS objective, and admits a polynomial-time greedy heuristic based on the MCKS problem for general objective functions.

## 4.3 Microsimulation Modeling

Team member Peter Stone has developed two open-source traffic simulation simulators for AVs: AIM, which provides highly detailed representations of small networks of intersections; and AORTA, which provides a more aggregate representation of a much larger (city-scale) network. Both accommodate mixed (traditional + CAV) traffic streams, traditional traffic control (signals), and reservation-based control for CAVs (who wish to reserve a safe path through the intersection without much delay).

The project objectives of the microsimulation modeling sub-task were defined as follows:

1. **Semi-AVs** - Inclusion of new, transitional vehicle types. The transition from current technologies to CAVs will occur gradually (along with retrofitting and addition of smart devices on board conventional vehicles), with vehicles gaining increasing autonomy and connectivity. For instance, a vehicle may have the ability to autonomously follow the car in front of it by staying in its lane and maintaining a constant following distance while traveling between intersections, but require a human driver to steer while turning through an intersection. We intend to adapt both AIM and AORTA to be able to model traffic that includes a mix of HVs, semi-AVs, and fully-AVs.
2. **Extending intersection control to handle mixed technology levels** - In the case of vehicles that can follow autonomously, but not steer, such vehicles may be able to communicate with the intersection manager and obtain a reservation in more limited circumstances than a vehicle with higher autonomy. For the case of HVs, we aim to add traffic light signaling that will coexist with the autonomous intersection management, thus allowing communication with both human drivers and AVs. These settings will be coded into the existing software, allowing for a wide range of scenario analyses under this sub-task.

As a first step in this research, we evaluated the appropriateness of both AIM and AORTA as simulations of mixtures of HVs, semi-AVs, and fully AVs. We found that the AIM simulator is well-suited to such an adaptation due to its prior modeling of both fully AVs and HVs. We therefore determined that it was feasible to implement a variety of hybrid types of semi-AVs and study a range of traffic mixtures as described below. On the other hand, we found that the AORTA simulator does not meaningfully distinguish between HVs and AVs, and we did not see a straightforward path to implementing the sort of studies proposed in this task within AORTA. We therefore focused our subsequent research efforts associated with this task entirely on the AIM simulator.

### 4.3.1 Autonomous Intersection Management

The objective of the original *Autonomous Intersection Management* (AIM) project was to create a scalable, safe, and efficient multiagent framework for managing AVs at intersections. AIM is designed for a time when all vehicles will be fully autonomous. The AIM protocol exploits the fine control of AVs to allow more vehicles simultaneously to cross an intersection, thus effectively reducing the delay of vehicles by orders of magnitude compared to traffic signals (2011).

In order to test the impact of the AIM protocol the AIM simulator was developed. The AIM simulator validated that by leveraging the control and network capabilities of AVs the AIM intersection control protocol is much more efficient compared to traditional traffic signals (2014).

*Summary of Work*

In order to achieve the above objectives with regards to AIM, the research focused on two main sub-objectives:

- **SemiAIM Protocol** - We devised an enhanced version of the AIM protocol denoted SemiAIM. As opposed to the AIM protocol, the SemiAIM protocol can correspond with semi-AVs and HVs as well as fully AVs. Figure 4.9 summarizes the interaction model of the SemiAIM protocol between human drivers, driver agents (with AV or semi-AV capabilities), and the Intersection Manager (IM). We require the inclusion in the vehicle of a single button that signals the driver agent to ask for a reservation. After pressing the button, the driver agent will automatically send a request message to the IM on behalf of the human driver. It is also important that there is a clear Okay indicator (such as a green light) installed in the car that indicates when the request has been confirmed. After seeing the Okay signal, the driver would have to actively pass control to the driver agent, again by pressing a single button. This way the driver will not be surprised by any sudden autonomous actions of the vehicle. The driver's involvement in this procedure depends on the level of autonomous capabilities installed in the car. The different classifications of autonomous capabilities are described in Table 4.5. SemiAIM only requires the human driver to perform relatively simple driving maneuvers such as holding the steering wheel at a certain angle (types SA-ACC and SA-CC vehicles) or driving as if under a traffic signal (type SA-Com vehicles). These tasks are much simpler than other maneuvers such as lane changing and passing other vehicles, and thus should not be taxing to experienced human drivers.
- **SemiAIM Simulator** - In order to experiment with the SemiAIM protocol we developed the SemiAIM simulator. Based on the AIM simulator, SemiAIM is able to simulate semi-AVs and HVs as well as fully AVs. Using the SemiAIM simulator, we have performed experiments to test the efficiency of the SemiAIM protocol. We observed that (as expected) as the percentage of cars with autonomous capabilities increases then each vehicle suffers less delays. Figure 4.10 presents the average delay per car while crossing the intersection (y-axis) against the ratio of AVs/HVs (x-axis) for different types of autonomous capabilities. Traffic level was fixed to 360 vehicles/lane/hour.

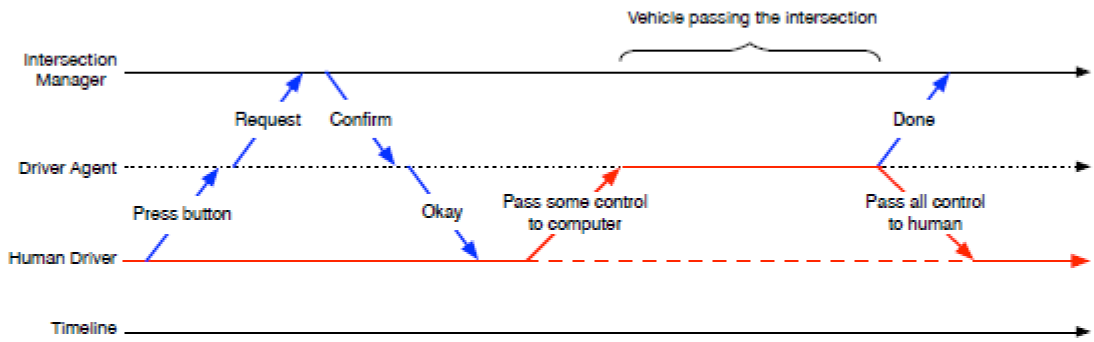



*Figure 4.9: The Interaction between Human Drivers, Driver Agents, and the IM. (The blue lines are message passing, and the red lines are transfer of control. Note that human drivers retain some control of the vehicle inside the intersection [the dashed red line]).*

**Table 4.5: Semi-autonomous Vehicle Technologies**

| Vehicle Type | Communication Device | Cruise Control | Adaptive Cruise Control |
|---|---|---|---|
| SA-ACC | X | X | X |
| SA-CC | X | X | |
| SA-Com | X | | |

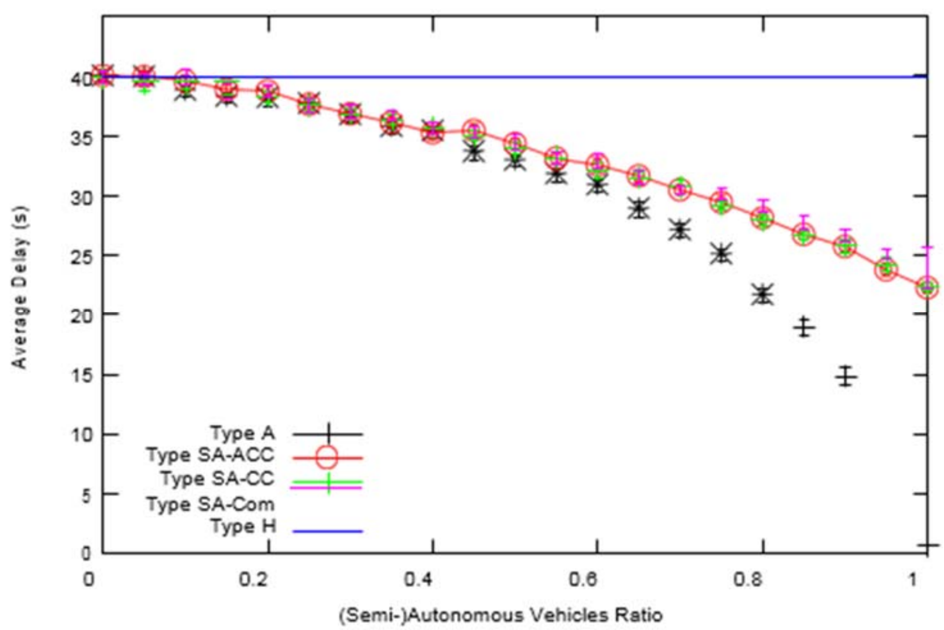



*Figure 4.10: Average Delay (y -axis) vs. Different Ratio of Autonomous/Human Drivers (x - axis). Note: Traffic level = 360 vehicles/lane/hour.*

### 4.3.2 Dynamic Traffic Assignment Methodology

DTA models have become a widely accepted tool to support a variety of transportation network planning and operation decisions. The ability of these models to produce stable and meaningful solutions is crucial for practical applications, particularly for those involving the comparison of modeling results across multiple scenarios. DTA is particularly relevant for modeling AVs because AVs affect many time-dependent variables. For instance, unlike fixed-phase traffic signals, reservation-based intersection efficiency is highly dependent on the demand at each approach and will vary over time. In addition, when mixed (AV and HVs) flows are considered, time-varying proportions of AVs on a road will result in the road capacity changing over time. Therefore, DTA is used for some of the most critical modeling for Task 4. This section describes the solution methodology used for solving DTA.

Two main processes are repeated multiple times during the solution of an SBDTA framework: the simulation of traffic conditions for a given assignment of vehicles to paths, and the search for new shortest paths based on the simulated traffic conditions. Both may involve significant computational effort, depending on the characteristics of specific SBDTA implementations. The computational efficiency of the analyzed techniques is not explicitly described, as it will highly depend on implementation-stage decisions that involve other components of a SBDTA model.

*User Equilibrium in Simulation-Based DTA Models*

The typical solution framework for SBDTA models seeks to attain UE conditions. UE is based on Wardrop (1952) and is related to equilibrium strategies of game theory. It refers to a state in which no traveler can improve his or her travel time by switching paths. For STA models with link performance functions, UE is typically found by solving a convex program. When the link performance functions are monotone increasing with link flow, the solution to the convex program is unique and exists. For SBDTA, travel times are determined by simulation, and travel times depend on departure time due to traffic congestion waves that evolve over time. Therefore, SBDTA solves for a modified UE state known as a dynamic user equilibrium (DUE), in which travelers only consider travel times of paths for their specific departure time. Furthermore, travel times are not well-behaved functions of link flows. Therefore, proving that a DUE exists, or is unique, is not possible. In practice, though, many of the algorithms used for STA convergence have been shown to be effective for DTA.

To find UE, many STA models have relied on the MSA as described in Sheffi (1985), which has been shown to converge to the equilibrium solution in STA problems with well- behaved link-cost functions (Powell and Sheffi, 1982). The framework used for the static case may be easily extended to the solution of SBDTA problems. However, although MSA does not guarantee convergence for SBDTA due to the complex and discontinuous nature of link costs after accounting for traffic dynamics (Robbins and Monro, 1951), practical results indicate a convergence pattern.

*Simulation*

The simulation model of SBDTA is an approximation method to solving equations describing dynamic traffic flow, such as the kinematic wave theory (Lighthill and Whitham 1955; Richards 1956). The complexity has resulted in discrete solution methods such as the CTM (Daganzo 1994, Daganzo 1995) and the link transmission model (Yperman 2007). The models are solved by iterating through discrete time steps and updating flows accordingly. SBDTA can model continuous or discrete flow, and does not introduce stochastic driver behavior. Given roadway parameters, flow route, and departure time choice, simulation output is deterministic. For the methodology of this task, the SBDTA for this task uses the multi-class CTM described above.

*Solution Framework*

In the context of DTA, MSA algorithms involve finding the time-dependent shortest paths under prevalent conditions and shifting a pre-determined fraction of vehicles to such routes. The fraction of vehicle sot be re-assigned, called the step size, decreases as the algorithm progresses, and is equal to $\frac{1}{n}$ (where $n$ is the iteration number) for all ODTs.

SBDTA models are typically chosen for practical applications over their analytical counterparts, which are typically suitable only for the study of very small networks. Moreover, SBDTA models are appealing because they can realistically capture the impact of a variety of traffic control devices, network operation strategies, and time dependent changes in traffic conditions. Typical SBDTA frameworks include three main components: a traffic simulator, a path generator, and an assignment module. A traffic simulator is used to evaluate the network performance based on a specific assignment of vehicles to paths. The path generator uses simulation results to find the time-dependent least-cost path under prevalent conditions per OD pair and assignment interval tuple (ODT). The assignment module adjusts the allocation of vehicles to paths with the goal of attaining DUE. Assignment often follows an iterative approach based on updated travel times from the traffic simulator. Initially, a certain number of cars are prescribed for paths that have the least amount of travel time. The simulator runs and determines the travel times for each path. New paths are created by the path generator that perform better than the previous iteration and the assignment module, based on some predetermined method, takes a certain volume of vehicles from one path and places them in others. This process is visually represented in Figure 4.11.

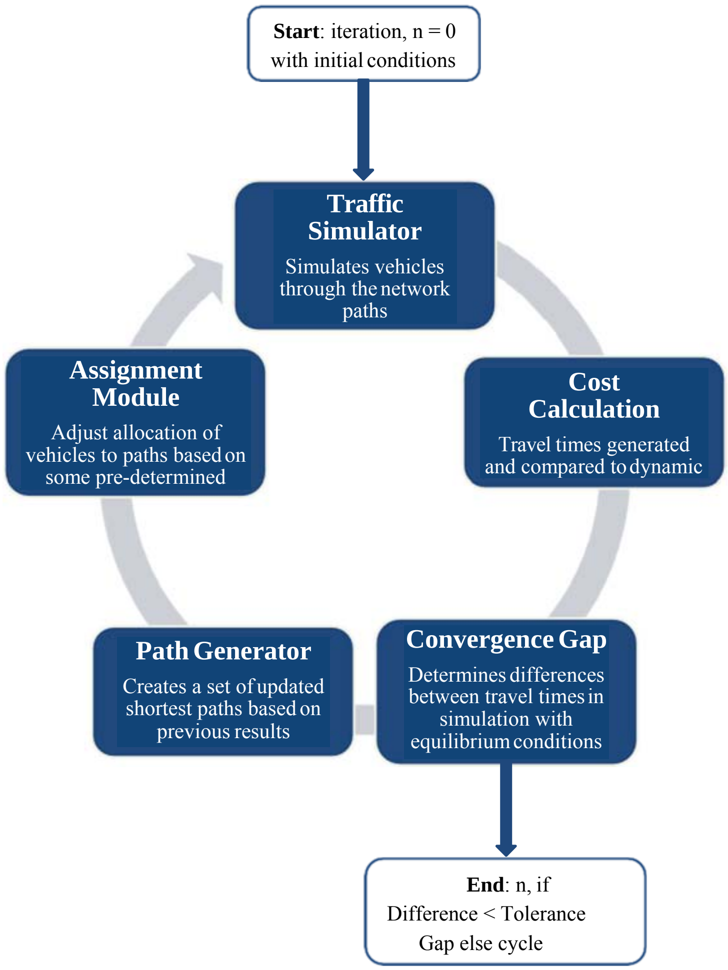



*Figure 4.11: Process of SBDTA Framework*

This process continues until the convergence criteria is met which is determined by Eq. 4.79. Convergence criteria are assessed and the assignment of vehicles to paths is adjusted based on some pre-defined logic. The process is repeated until an acceptable solution is found. In order to evaluate convergence, most SBDTA applications define a gap function that measures the proximity of a given solution to the equilibrium conditions. SBDTA models differ mostly in the type and refinement of the selected traffic simulator, and on the rationale behind the assignment adjustments.

$$\gamma(i) = \frac{\sum_{(r,s,t)\in Z^2 xT} \sum_{\pi\in\Pi_{rs}} (c_t^{\pi} - C_{rst}) h_t^{\pi}}{\sum_{(r,s,t)\in Z^2 xT} \sum_{\pi\in\Pi_{rs}} c_t^{\pi} h_t^{\pi}} \tag{4.79}$$

### 4.3.3 Test Networks Used for Link-Based Meso-Simulations

This section presents the test networks used in the multiclass CTM meso-simulation to model the effects of CAVs on congestion and different types of road networks. These networks included two arterial networks, three freeway networks, and one downtown city network. These networks are also among the top 100 congested roadways in Texas, which made them particularly interesting candidates for observing the effects of CAVs on congestion and traffic (TxDOT 2015).

*Arterial Networks*

Two arterial networks, including the intersection of Lamar and 38th Street as well as a strip of Congress Avenue, were used for simulations and are shown in Figure 4.12. The first arterial network, Lamar & 38th Street, contains the intersection between the Lamar & 38th Street arterials, as well as five other local road intersections. This network contains 31 links, 17 nodes, and 5 signals—with a total demand of 16,284 vehicles over a 4-hour time window. Congress Avenue in Austin was also studied. This network has a total of 25 signals in the network, 216 links, and 122 nodes with a total demand of 64,667 vehicles in a 4-hour period. These arterial networks used fixed-time signals for controlling flow along the entire corridor.

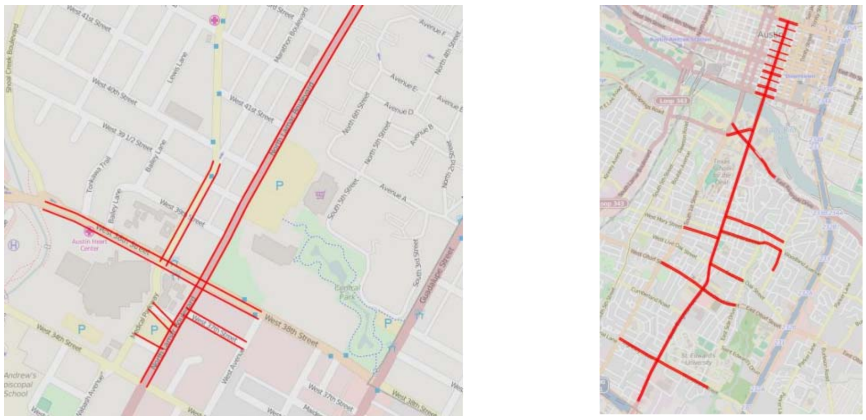


*Figure 4.12: Lamar and 38$^{th}$ Street and Congress Avenue Networks (from left to right)*

*Freeway Networks*

The three total freeway networks are shown in Figure 4.13. The first freeway network is the I-35 corridor in the Austin region, which includes 220 links and 220 nodes with a total demand of 128,051 vehicles within a 4-hour span. (Due to the length, the on- and off-ramps are difficult to see in the image.) All intersections are off-ramps or on-ramps. The I-35 network is by far the most congested of the freeway networks and one of the most congested freeways in all of Texas, especially in the Austin Region. The US-290 network in the Austin region was studied, with 97 links, 62 nodes, 5 signals, and a total demand of 11,098 vehicles within 4 hours. Finally, research was conducted on Texas State Highway Loop 1, also known as the MoPac Expressway after the Missouri Pacific Railroad that runs alongside the expressway, in the Austin region. This network contains 45 links, 36 nodes, and 4 signals with a total demand of 27,787 vehicles within 4 hours. On this network, there are a mixture of merging and diverging ramps and signals, which allows for some interesting analyses. This network was chosen due to the large number of signals around the freeway. All freeway networks are also among the 100 most congested roads in Texas (TxDOT 2015).


*Figure 4.13: I 35, Hwy 290, and MoPac Networks (from left to right)*

*City Networks*

The last network studied was the Austin downtown network (Figure 4.14), as this would be the largest network tested to show us the effects of TBR and CAVs as they apply to an entire downtown structure. Downtown Austin differs from the previous networks in that there are many route choices available. Therefore, DTA was solved using the method of successive averages, a method that assigns vehicles to paths based on the iteration number in order to obtain an optimal system path for the vehicles. All scenarios were solved to a 2% gap, which was defined as the ratio of average excess cost to total system travel time. This gap was deemed sufficient to return the realistic results. Any decrease in the gap would incur larger amounts of computation time that would not alter the results significantly. Route choice admits issues such as the Braess and Daganzo paradoxes (1968, 1998), in which capacity improvements induce selfish route choice that increase travel times for all vehicles. The downtown network also contains both freeway and arterial links, with part of I-35 on the east side, a grid structure, and several major arterials.

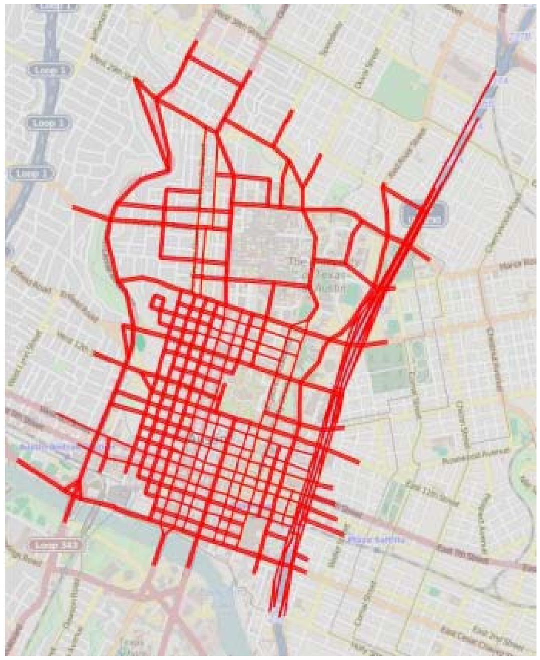


*Figure 4.14: Downtown Austin Network*

### 4.3.4 Effects of Autonomous Vehicles on Networks

This section presents results of the DTA simulation to analyze the effects of different proportions of CAVs on a network with human drivers. In addition, simulations were run with 100% CAVs using a TBR system on chosen test networks to see if there were travel time improvements in comparison with those of typical traffic signals. The results were analyzed by comparing travel times in vehicles/minute as well as the total travel time (TTT) of all vehicles in the network. The two main objectives of these simulations were to measure the effects on congestion of increasing the proportion of CAVs to HVs and of implementing a TBR system instead of a traditional signal system with 100% CAVs.

It is important to note that these simulations assume zero pedestrians and cyclists, along the routes and at intersections. Non-instrumented, non-motorized travelers using crosswalks will disrupt intersection operations and reduce vehicle flows. Both pedestrians and cyclists will probably not be able to use the tiles in TBR system, unless they wear special glasses (giving path and timing requests to them), they can be trusted to follow the guidance, and their slower speeds are accounted for.

In most simulations, perception reaction times of 0.5s and 1s were assumed for CAVs and HVs respectively, however, these times can be seen as something to be achieved farther into the future by autonomous vehicles whereas reaction times of 1s and 2s for CAVs and HVs respectively is a nearer and more achievable goal presently. Due to this ideology, several simulations were run using these 1s and 2s reaction times including the following networks: I-35, MoPac Expressway, Lamar & 38$^{th}$ Street, and Congress. After running simulations, it was observed that the slower perception reaction times showed the same trends and most of the time, nearly the same travel times with a few exceptions. For these reasons, only the previously listed four networks were simulated using the 1s and 2s reaction times. The purpose of these simulations involving analyzing effects of reaction times is to observe changes in road capacity as these reaction times can reduce following headways and backwards wave propagation. Capacities for HVs have been directly taken from models calibrated for VISTA.

*CAV Effects on Arterial Networks*

The travel time results for arterial networks are shown in Figure 4.15. The general trend for the arterial networks is that the use of the TBR reduced travel times. Although reservations helped most arterial networks, such as Congress Avenue, at high demands the reservations increased travel times for Lamar & 38th Street. The lower 0.5-second reaction time for CAVs, compared to the 1-second reaction time for HVs, decreased travel times for every network tested. The 1s and 2s reaction times also decreased travel times for every network tested and followed similar trends for traditional signal systems with CAVs. However, the slower perception reaction times decreased travel times under the TBR system more so than with the faster 0.5s and 1s reaction times. This is primarily because 1s and 2s reaction times results in a greater benefit from CAVs relative to HVs, compared with 0.5s and 1s reaction times. As the proportion of CAVs in the network was increased, the travel times decreased. Reduced reaction times were more beneficial in some scenarios than in others, but all yielded a benefit. The reaction time difference was analyzed by running simulations of each network at a moderate 85% demand and by changing the proportion of CAVs ranging from 0%-100%.

In the Lamar & 38th Street network, the TBR significantly decreased travel times for a 50% demand simulation as compared to traffic signals at 50% demand; however, once the demand was increased to 75%, reservations began increasing travel times relative to signals. This is most likely due to the close proximity of the local road intersections. On local road-arterial intersections, the FCFS reservations grant greater capacity to the local road than traffic signals. Because these intersections are so close together, reservations likely induced queue spillback on the arterial with the larger capacity. The longer travel times might also be linked by reservations removing signal progression on 38th Street. During high congestion, FCFS reservations tended to be less optimized than signals for the local road-arterial intersections. On the other hand, during low demand, intersection saturation was sufficiently low for reservations to reduce delays and travel times.

The Lamar & 38th Street network responded well to an increase in the proportion of CAVs with dramatic decreases in travel times, due to the CAV low reaction times. At 85% demand and at 25% CAVs, the TTT was reduced by 50%, and when all vehicles were CAVs, the TTT was reduced by 87%. Each demand proportion was then simulated with only CAVs. As demand increased, the improvements from reduced reaction times also increased. At 50% demand, reduced reaction times decreased travel times by 44%, whereas at 100% demand, reduced reaction times decreased travel times by 93%. The effect of greater capacity improved as demand increased because as demand increased, the network became more limited by intersection capacity. At low congestion (50% demand), signal delays hurt travel times because reservations made significant improvements. At higher congestion, intersection capacity was the major limitation and, therefore, reduced reaction times were of greater benefit.

Congress Avenue responded well to the introduction of reservations, showing decreases in travel times at all demand scenarios. These improvements are due to the large amount of streets intersecting Congress Avenue, each with a signal not timed for progression. The switch to reservations therefore reduced the intersection delay. However, the switch to reservations could result in greater demand on this arterial in the future. Included in these simulations were the effects of route choice in the downtown Austin network (Section 24.3).

CAVs also improved travel times and congestion due to reduced reaction times. At 85% demand, using reaction times of 0.5s and 1s for CAVs and HVs respectively, a 25% proportion of CAVs on roads decreased travel times by almost 60%. This increased to almost 70% reduction in travel time when all vehicles were CAVs. On Lamar & 38th Street, as demand increased, the reductions in travel times increased as well due to the CAV reaction times. For example, at a 50% demand level, the Lamar and 38th Street interchange experienced decreased travel time by about 10% when all vehicles were modeled as CAVs. The same network at 100% demand and assuming all vehicles are CAVs, reduced the travel time by nearly 82%. The reduced reaction times did not improve travel times as much as TBR, however—except for the 100% demand scenario. This indicates that at lower demands, high travel times were primarily caused by signal delay. However, travel time was still improved by lower CAV reaction times.

It is important to note that, except in the case of %100 CAVs with TBR, the reduced travel time and congestion is exclusively due to the reduced reaction time of 0.5s for CAVs, versus 1s for HVs, allowing for reduced following headway. Effectively, this allows for higher throughput for both links and intersections by increasing the maximum density of vehicles. This is an important assumption to the analysis, but it may not be valid in the early stages of CAV adoption. While CAVs will experience reduced reaction times relative to HVs, it is likely that, either due to transportation norms, an abundance of caution on behalf of manufactures, or issues with integrating CAVs with HVs, CAVs will not realize reduced following headways until CAV adoption is quite high. If it is the case that CAVs do not realize reduced headways, then average travel times and congestion will not decrease due to the presence of increased numbers of trips brought about by the lower cost of travel for CAVs and the presence of CAV round-trips. Fundamentally, if CAV behavior mimics that of HVs, then using existing infrastructure and intersection management policies is unlikely to lead to lower average travel times or reduced congestion. However, the results presented here assume that CAVs can take full advantage of their reduced reaction times.

Overall, these results show consistent, significant improvements from reduced reaction times of CAVs at all demand scenarios. As shown in Figure 4.15, reducing the reaction time to 0.5 seconds nearly doubles road and intersection capacity. However, the effects of reservations were mixed. At low congestion, traffic signal delays had a greater effect on travel time, and in these scenarios reservations improved the traffic flow. Reservations also improved the traffic flow when signals were not timed for progression (although this may be detrimental to the overall system). However, as seen on Lamar & 38th Street, during high demand, reservations performed worse than signals, particularly around local road-arterial intersections.

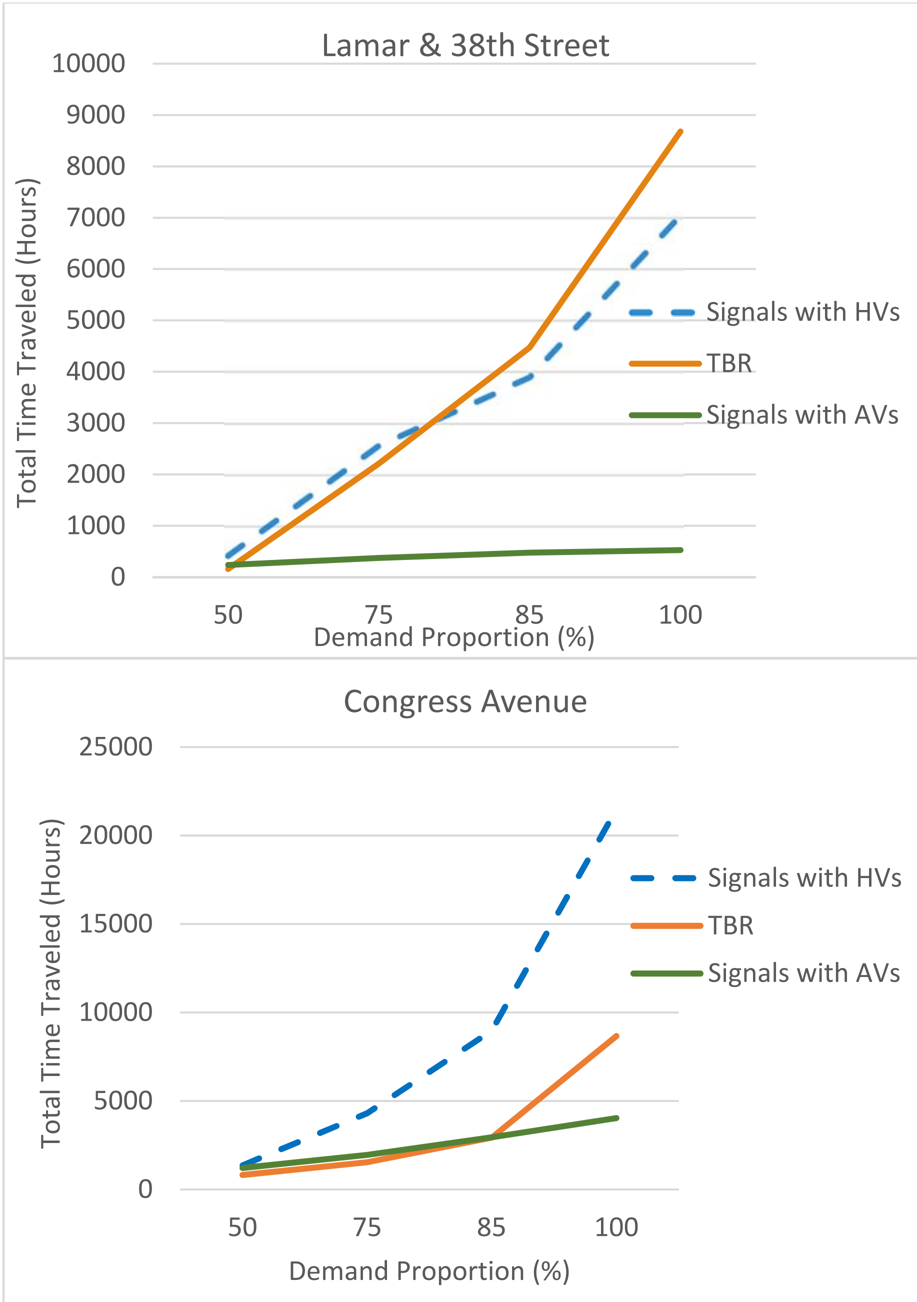



*Figure 4.15: Arterial Network Travel Time Results for Lamar & 38th Street and Congress Avenue*

*CAV Effects on Freeway Networks*

Results for the freeway networks are presented in Figure 4.16. Although there were some observed improvements in travel times for the US-290 network using reservations, the improvements were modest. On the other hand, observing the I-35 and MoPac networks, reservations made travel times worse for all demand scenarios. Most of the access on US-290 is controlled by signals, which explains the improvements observed when reservations were used there. Reservations seem to have worked more effectively with arterial networks, probably because on- and off-ramps do not have signal delays. Therefore, the potential for improvement from reservations is smaller.

Overall, greater capacity from CAVs' reduced reaction times improved travel times in all freeway networks tested, with better improvements at higher demands. Reduced reaction times improved travel times by almost 72% at 100% demand on I-35. On US-290 and I-35, as with the arterial networks, the improvement from CAV reaction times increased as demand increased. This is because freeways are primarily capacity restricted and the faster reaction times increase this capacity. On MoPac, reaction times had a smaller impact, but the network overall appeared to be less congested.

Links and nodes were chosen to study how reservations affected travel times at critical intersections or spans on the freeways, such as high demand on- or off-ramps. For these specific links, average link travel times were compared between 120 and 135 minutes into the simulation, at the peak of the demand. Researchers compared HVs, CAVs with signals, and different CAV proportions with signals at 85% demand, which resulted in moderate congestion. In the I-35 network, very few changes in travel times for the critical groups of links were observed from the different intersection controls.

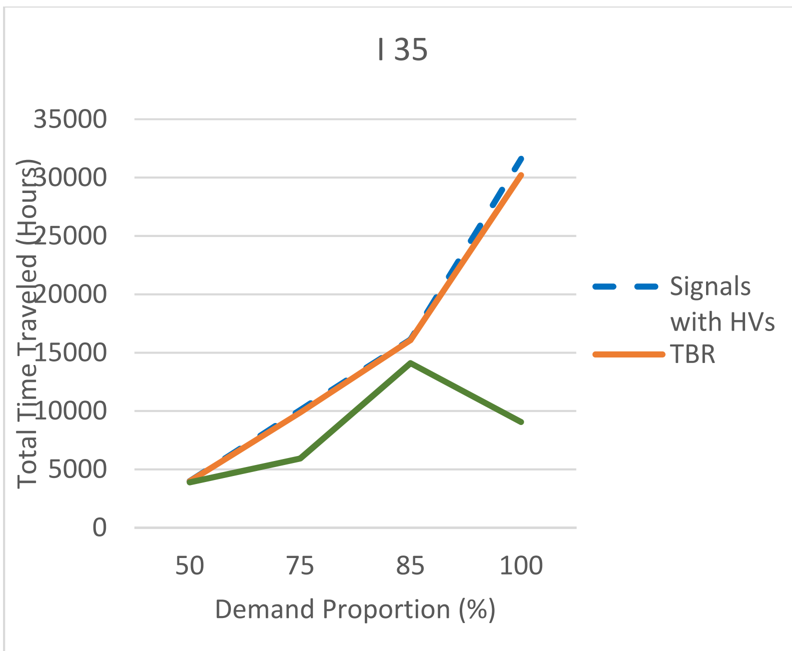



*Figure 4.16: Freeway Network Travel Time Results for I-35*

The differences appear greater in the US-290 corridor with more overall improvements in critical groupings of links near intersections. Interestingly, the largest improvements in travel times going from traffic signals to reservations occurred at queues for right turns onto the freeway. A possible explanation for this result is that making a right turn conflicts with less traffic than going straight or making a left turn. Although signals often combine right-turn and straight movements, reservations could combine turning movements in more flexible ways. Although larger improvements in travel times occurred at the observed right turns, improvements at left turns were also observed. Because US-290 has signals intermittently spaced throughout its span, vehicles are frequently stopping at lights causing signal delays, which can increase as the demand increases.

Using the reservation system, the flow of traffic is stopped less frequently, if at all, reducing congestion along the freeway. Also, in the 290 network, analyzing the effects of reduced reaction times showed that improvements to travel times were made due to the reaction times and their respective capacity increases, but these improvements were less than those experienced due to reservations. It is also important to note that the use of 1s and 2s reaction times rather than 0.5s and 1s reaction times for the CAVs and HVs respectively did not affect travel times or any trends seen in the original reaction time simulations. In most cases, using reservations instead of signals doubled the improvements resulting from using CAVs. Reservations appear to have a positive effect on traffic flow and congestion in networks (freeway and arterial) that use signals to control intersections.

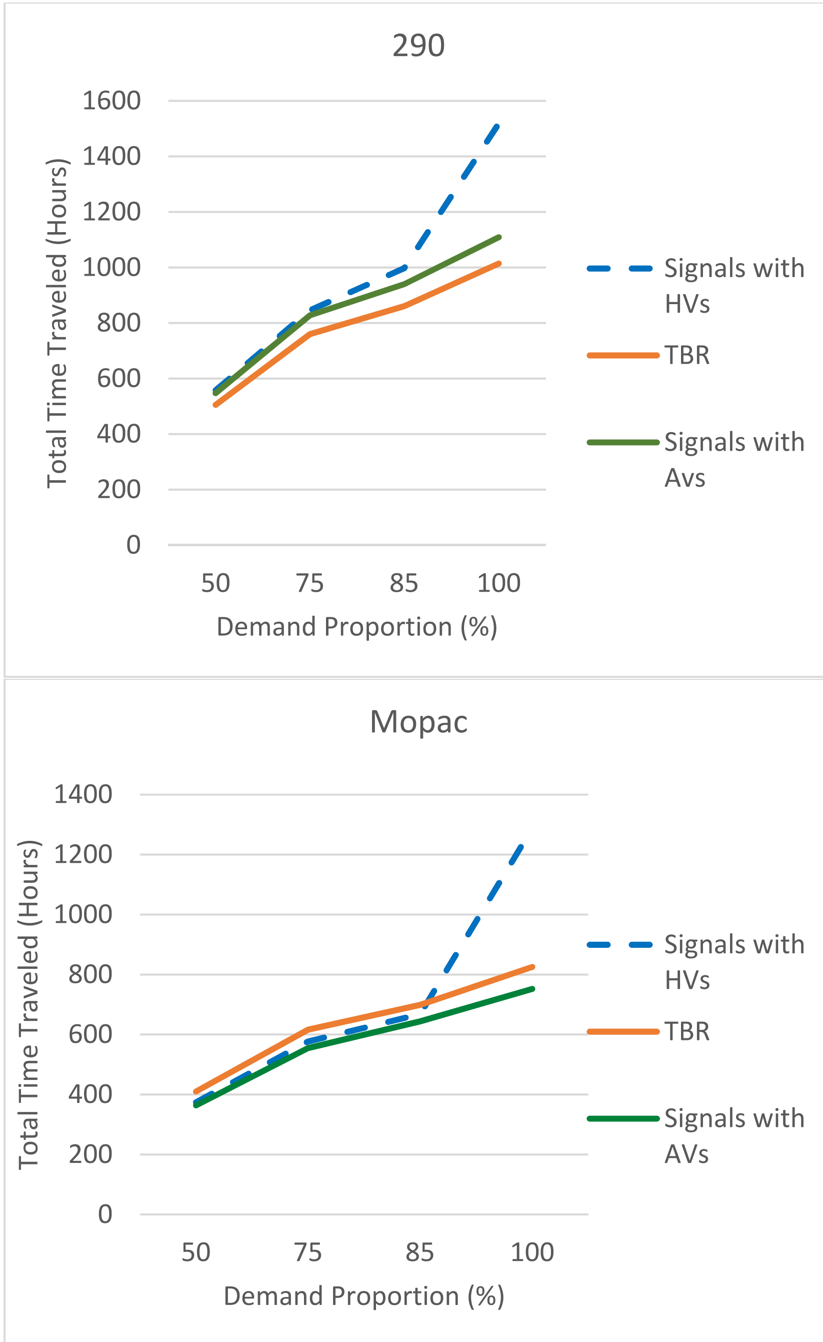



*Figure 4.17: Freeway Network Travel Time Results for MoPac and US 290*

*CAV Effects on City Networks*

Tests were performed on the downtown network of Austin with 100% demand at different proportions of CAVs in a traditional signal system, as well as with the TBR system, as shown in Table 4.6. Downtown Austin differs from the previous networks in that many route choices are available. Therefore, DTA was solved using the method of successive averages. All scenarios were solved to a 2% gap, which was defined as the ratio of average excess cost to total system travel time. Route choice admits issues such as the Braess and Daganzo paradoxes (1968, 1998), in which capacity improvements induce selfish route choice that increase travel times for all vehicles. The downtown network also contains both freeway and arterial links, with a section of I-35 on the east side, a grid structure, and several major arterials.

Reservations greatly helped travel times and congestion in the downtown network, cutting travel times by an additional 55% at 100% demand. When combined with reduced reaction times, the total reduction in travel time was 78%. Reservations were highly effective in downtown Austin—more effective than in the freeway or arterial networks, even under high congestion. In downtown Austin, most intersections are controlled by signals with significant potential for improvement from reservations. Although many intersections are close together, congested intersections might be avoided by dynamic user equilibrium route choice decisions, avoiding the issues seen with reservations in Lamar & 38$^{th}$ Street. The increased capacity from 100% CAVs also contributed to much less congestion, reducing travel times by around 51%.

**Table 4.6: Downtown Austin City Network Travel Time Results**

| Downtown Austin | | | | |
|---|---|---|---|---|
| **Simulation Type** | **Demand** | **Proportion of CAVs** | **TTT (hr)** | **min/veh** |
| Signals | 100% | 0 | 18040.2 | 17.23 |
| Signals with CAVs | 100% | 0.25 | 13371.4 | 12.77 |
| Signals with CAVs | 100% | 0.5 | 11522.3 | 11 |
| Signals with CAVs | 100% | 0.75 | 9905.1 | 9.46 |
| Signals with CAVs | 100% | 1 | 8824.7 | 8.43 |
| TBR Reservation System | 100% | 1 | 3984.3 | 3.8 |

As mentioned earlier, all these simulations assume zero pedestrians and cyclists, along the routes and at the intersections. Non-instrumented, non-motorized travelers using crosswalks will disrupt intersection operations and reduce vehicle flows. Both pedestrians and cyclists will probably not be able to obtain a reservation within the TBR system, unless they wear special glasses (giving path and timing requests to them), they can be trusted to follow the guidance, and their slower speeds are accounted for.

## 4.4 Shared Autonomous Vehicles

### 4.4.1 Shared Autonomous Vehicle Framework

This section presents a general framework for dynamic simulation of SAVs to admit the latest developments in traffic flow modeling and SAV behavior. The framework is built on two events that can be integrated into most existing simulation-based traffic models. The purpose of this framework is to encourage future studies on SAVs to make use of existing traffic models for effective comparisons with current traffic conditions. As we will demonstrate in our case study, replacing personal vehicles with SAVs for the same number of travelers could increase congestion. To determine whether SAVs are beneficial, it is therefore necessary to compare SAV and personal vehicle scenarios in the same traffic model.

In this section, we discuss the key events defining this framework and the types of responses they warrant. However, the specific responses depend on the dispatcher logic, and for generality we do not require specific dispatcher behaviors. This framework is based on a traffic simulator operating on a *network* $G = (N, A, Z, V, D)$, where $N$ is the set of nodes, $A$ is the set of links, and $Z \subset N$ is the set of centroids. The network has a set of SAVs $V$ that provide service to the demand $D$. Note that $D$ is in terms of person trips, not vehicle trips, since travelers will be serviced by SAVs. The integration of the framework with the traffic simulator is illustrated through the simulator logic in Figure 4.18 with simulator time $t$ and time step $\Delta t$. Events and responses are indicated with double lines; the remainder is the standard traffic simulator. The simulation steps are grouped into three modules: 1) demand; 2) SAV dispatcher; and 3) traffic flow simulator. The remainder of this section discusses these modules in greater detail.

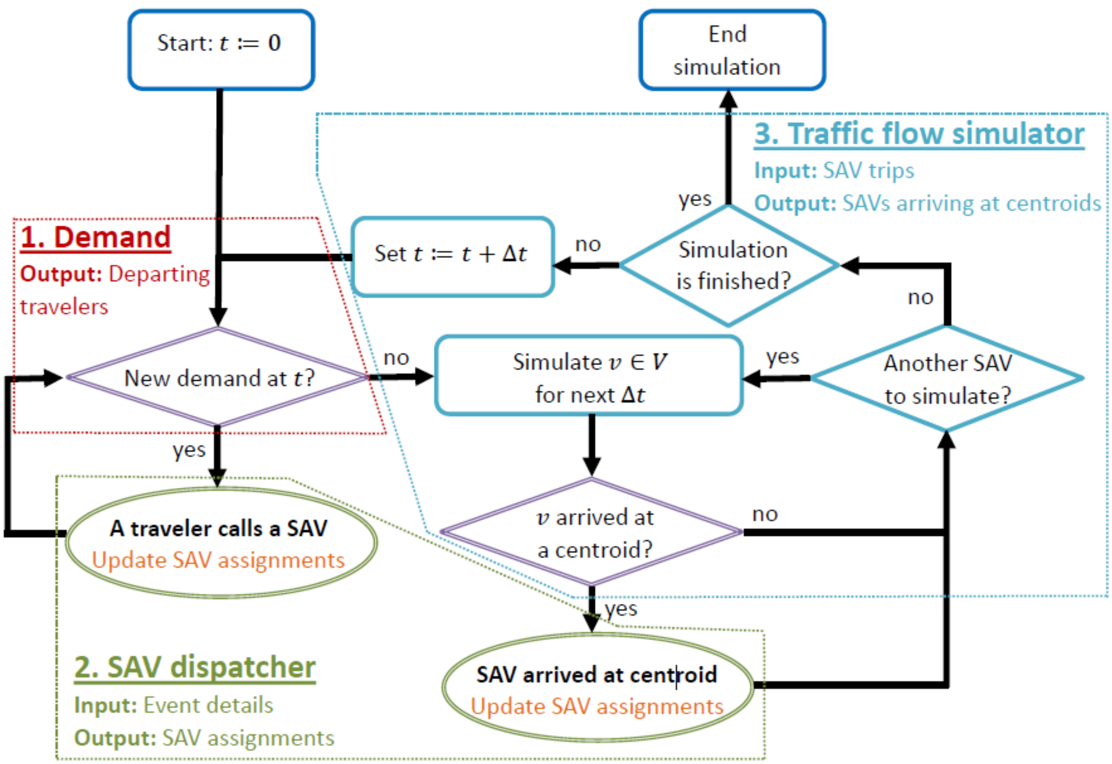



*Figure 4.18: Event-based Framework Integrated into Traffic Simulator*

*Demand*

The demand module introduces demand into the simulation and outputs the set of travelers that request an SAV at time $t$ (This does not include waiting travelers). The demand module of existing traffic simulators may be adapted for this purpose, with the caveat that the demand is in the form of travelers, not personal vehicles. If new demand appears at $t$, this triggers the corresponding event: a traveler calls an SAV. Because SAV actions are triggered by a traveler calling an SAV, this framework admits a very general class of demand models. The major requirement is that demand must be separated into packets that spawn at a specific time with a specific origin and destination. Although in this paper we primarily refer to demand as individual travelers, these packets could also represent a group of people traveling together. Demand cannot be continuous over time because that would trigger a very large number of events. However, in our case study demand and traffic flow are simulated at a time step of 6 seconds, which is demonstrated to be computationally tractable for city networks.

As a result, this framework can handle both real-time and pre-simulation demand generation. Real-time demand may be randomly generated every simulation step, triggering the event of a traveler calling an SAV when the demand is created. For models with dynamic demand tables, each packet of demand spawns at its departure time and calls an SAV then. In addition, if demand is assumed to be known prior to its departure time, SAVs may choose to preemptively relocate before the traveler appears. However, this requires that travelers plan ahead to schedule an SAV before they depart. A less restrictive assumption is that the productions at each zone are known, and SAVs may preemptively relocate in response to expected travelers. This requires less specific information about the traveler, and trip productions are usually predicted by metropolitan planning organizations.

### *SAV Dispatcher*

For this framework, we assume the existence of an SAV dispatcher that knows the status of all SAVs and can make route and passenger assignments. With the range of wireless communication available today, the existence of a central dispatcher is a reasonable assumption for SAVs. However, if desired the dispatcher logic could also be chosen to simulate individual SAVs making decisions on their own limited information.

The SAV dispatcher module determines SAV behavior, including trip and route choice, parking, and passenger service assignments. The dispatcher operates as an *event handler* responding to the events of a traveler calling an SAV or an SAV arriving at a centroid, and takes as input the event details. The dispatcher is responsible for ensuring that all active travelers are provided with SAV service.

The output of the dispatcher is the SAV behaviors in response to the event. These include SAV vehicle trips (which are passed to the traffic flow simulator), passenger pick-up and drop-off, and parking SAVs that are not needed. At any given time, each SAV is either parked at a centroid or traveling. If an SAV is parked, its exact location must be known.

This framework is event-based, meaning that SAV actions are assigned when one of the following events occurs:

1. A traveler calls an SAV.
2. An SAV arrives at a zone centroid.

The first event is triggered in response to demand departing (or requesting to depart), and the second is in response to an SAV completing its assigned trip. These can be implemented in most simulation-based frameworks. Instead of a traveler departing by creating a personal vehicle, the traveler calls an SAV. When an SAV completes travel on a path (which should end in a centroid), this also triggers an event so the simulator can check for arriving or departing passengers at that centroid and assign the SAV on its next trip.

### *A Traveler Calls an SAV*

When a traveler $d \in D$ calls an SAV, the dispatcher should ensure that the demand will be satisfied by an SAV. This could occur in several ways:

1. If an empty SAV $v \in V$ is parked at $d$'s origin, the dispatcher might assign $v$ to

immediately pick up $d$.

2. If an empty SAV $v \in V$ is parked elsewhere, the dispatcher may assign $v$ to travel to $d$'s origin. In this case, the dispatcher might choose to wait to optimize the movement of SAVs. For instance, Fagnant & Kockelman (2014) use a heuristic to move SAVs to a closer waiting traveler rather than the first waiting traveler. The dispatcher might also change the path of a traveling SAV to handle the demand.
3. If an SAV $v \in V$ is inbound to $d$'s location, the dispatcher might assign $v$ to service $d$ if possible. However, the dispatcher should consider $v$'s estimated time of arrival (ETA). If $v$'s ETA results in unacceptable waiting time for $d$, the dispatcher may also send an empty SAV to $d$ in order to reduce waiting time.

Regardless of the conditions chosen for each action, the dispatcher must ensure that the demand will be handled.

*An SAV Arrives at a Centroid*

When an SAV $v \in V$ arrives at a centroid $i \in Z$, it has finished its assigned trip. This should result in two types of actions. First, if $v$ is carrying any travelers destined for $i$, they should exit $v$. Second, the dispatcher should assign $v$ to park at $i$ or depart on another trip. There are several possibilities for this assignment:

1. If $v$ still has passengers, it should continue to the next destination. If ride sharing is allowed and the capacity of $v$ permits it, other passengers at $i$ may wish to take $v$ to reduce their waiting time.
2. If $v$ is empty, and a traveler $d \in D$ is waiting at $i$ for an SAV, it is reasonable to assign $v$ to accept $d$. $v$ may then proceed directly to $d$'s destination or, if dynamic ride-sharing is allowed, to another centroid to pick up another passenger.
3. If no travelers are waiting at $i$ and $v$ is empty, the dispatcher might assign $v$ to pick up a traveler at a different centroid.
4. The dispatcher could also assign $v$ to wait at $i$ until needed for future demand, contingent on parking availability. If $i$ does not have available parking, $v$ cannot wait at $i$ and must travel elsewhere.
5. Finally, the dispatcher might assign $v$ to preemptively relocate to handle predicted demand.

The conditions given above are reasonable but may not be necessary. Optimizing the assignment of actions for the existing and predicted demand could use the possible actions in different ways. For example, $v$ might be assigned to park at $i$ and wait for expected demand even if $v$ is already carrying passengers. This optimization problem is similar to the class of vehicle routing problems, which are NP-hard. Therefore, solving this optimization is outside the scope of this paper, but we will study heuristic rules in later sections.

*Traffic Flow Simulator*

The traffic flow simulator takes as input SAV trips and their departure times and determines the arrival times of SAVs at centroids. The primary output of the simulator is to trigger the event that an SAV arrived at a centroid at the appropriate time.

Because the SAV framework is built on the events of a traveler calling an SAV, and an SAV arriving at a centroid, the framework admits many flow propagation models. The major requirement is that the model be integrated into simulation. After departing, an SAV travels along its assigned path until reaching the destination centroid, at which point it triggers the arrival event. Therefore, the framework must track the SAV travel times to determine arrival times, but its travel time may be evaluated by a variety of flow models. For instance, the travel time could be set as a constant or through link performance functions. Alternatively, SAV movement may be modeled through micro- or meso-simulation. Any uncertainty in the model is compatible with this framework; the SAV triggers the event only when it arrives at its destination. Note that this framework is compatible with other vehicles on the road affecting congestion through link performance functions or simulation-based flow propagation. Therefore, this SAV framework can be implemented with existing traffic models by modifying them to trigger demand and centroid arrival events. To demonstrate this flexibility, the case study implements this framework on the simulation-based DTA model of Levin & Boyles (2015a).

### 4.4.2 Case Study: Framework Implementation

This section describes the implementation of the SAV framework on a CTM-based traffic simulator. Although we discussed how to implement SAVs in existing traffic simulators, the responses of the dispatcher to events were not specified for generality. The purpose of this section is to describe the specific traffic flow simulator and dispatcher logic used in our case study, including the heuristics for dynamic ride-sharing and preemptive relocation.

In this case study, we assume that all vehicles are SAVs: travelers do not have personal vehicles available. This setting was chosen in order to study the feasibility of switching to an entirely SAV-based travel model. Furthermore, a mix of SAVs and personal vehicles would complicate the route choice. Finding routes for personal vehicles would require solving DTA, and the many simulations needed to solve DTA would add computation time and complexity to the theoretical model.

*Demand*

For this case study, we converted personal vehicle trip tables into SAV traveler trip tables. These trips are discretized with specific departure times. Although some of these vehicle trips may encompass multiple person trips, that information was not available. Furthermore, multiple persons using the same vehicle would likely use the same SAV. Therefore, it would only affect situations in which SAV capacity was a limitation, such as dynamic ride-sharing.

For each trip, the demand module creates a traveler at the origin at the appropriate time. Although the demand is completely known in advance, the SAV dispatcher is not programmed to take advantage of demand information. The dispatcher only responds to demand when a traveler is created.

*Traffic Flow Simulator*

The traffic flow simulator uses the CTM (Zhang et al. 2015, Lighthill and Whitham 1995), which is a space and time discretization of the hydrodynamic theory of traffic flow (Powell and Sheffi 1982, Robbins and Monro 1951). CTM has been used in, and allows direct comparisons with, large-scale DTA simulators (Daganzo, 1995). Because all vehicles are SAVs, we assume that intersections were controlled using the reservation-based protocol of Dresner & Stone (2004) for AVs. For computational tractability, we use the conflict region model of reservation-based intersection control proposed by Levin & Boyles (2015a).

DTA models typically assume that route choice is based on driver experience. Each vehicle individually seeks its shortest route, resulting in a DUE in which no vehicle can improve travel cost by changing routes. Although this concept is based on the analytical STA models, it requires further study to be formulated for SAV behavior because SAV trips may depend on stochastic demand. Therefore, we use a dynamic network loading-based route assignment. Let $\pi rs$ be the path stored by the dispatcher for travel from $r$ to $s$. When an SAV departs to travel from $r$ to $s$, it is assigned to the stored path $\pi rs$. During simulation, when $t \equiv 0 \; mod \; \Delta\mathcal{T}$, where $\Delta\mathcal{T}$ is the update interval, $\pi rs$ is updated to be the shortest path from $r$ to $s$ based on average link travel times over the interval $[t - \Delta\mathcal{T}, t)$. Our experiments use $\Delta\mathcal{T} = 1$ minute.

### *SAV Dispatcher*

This section describes the specific logic used to assign SAVs in our case study. Although this is only a heuristic for the vehicle routing problem of servicing all travelers, vehicle routing problems in general are NP-hard and solving them in real time is unrealistic. Instead, we describe reasonable behaviors that SAVs could choose.

### *A Traveler Calls an SAV*

When a traveler $d \in D$ calls an SAV at centroid $i \in Z$, we first check whether there are any SAVs already en-route to $i$. If an SAV en-route to $i$ is free, or will drop off its last passenger at $i$, and its ETA at $i$ is less than 10 minutes away, we allow that SAV to service $d$. This is to reduce the congestion that would result from sending more SAVs. (As we demonstrate below, moving SAVs more frequently can result in a net travel time increase while decreasing waiting times due to congestion.) If there are multiple travelers waiting at $i$, we assume that travelers get SAVs in a FCFS order — with some exceptions for dynamic ride-sharing. Therefore, we look at the ETA of the SAV that would be assigned to $d$, if one exists.

Otherwise, we search for the parked SAV that is closest (in travel time) to $i$. If it could arrive sooner than the ETA of the appropriate en-route SAV, it is assigned to travel to $i$ in order to provide service to $d$. This is a FCFS policy: the traveler that requests an SAV first will be the first to get picked up, even if the SAV could sooner reach a traveler departing later. Although Fagnant & Kockelman (2015) initially restricted SAV assignments to those within 5 minutes of travel to improve the system efficiency, FCFS is also a reasonable policy for dispatching SAVs. If all SAVs are busy, then $d$ is added to the list of waiting travelers $\mathcal{W}$.

### *An SAV Arrives at a Centroid*

If an SAV $v \in V$ is free after reaching centroid $i \in Z$ (either because $v$ is empty, or because $v$ drops off all passengers at $i$), and there are waiting travelers at $i$, then it is assigned to carry the longest waiting traveler. Note that $v$ may not be the same SAV that was dispatched to that traveler. Due to stochasticity in the flow propagation model, it is possible that the order of arrival of SAVs may differ. However, there is no significant difference between two free SAVs in terms of carrying a single traveler. Therefore, we assign them to travelers in FCFS order.

If $v$ still has passengers after reaching $i$ (which is possible when dynamic ride-sharing is permitted), then $v$ is assigned to travel to the next passenger's destination. However, travelers waiting at $i$ have the option of entering $v$ if it helps them in reaching their destination.

If $v$ is free after reaching $i$ and no demand is waiting at $i$, then $v$ is dispatched to the longest-waiting traveler in $\mathcal{W}$. If multiple SAVs become free at the same time, the one closest to the longest-waiting traveler in $\mathcal{W}$ will be sent. If $\mathcal{W}$ is empty, then $v$ will park at $i$ until needed. We assume for this study that centroids have infinite parking space, as there are no personal vehicles in this network. However, it would be possible to model limited parking by assigning $v$ to travel somewhere else if parking was not available at $i$.

*Dynamic Ride-sharing*

We also consider the possibility of dynamic ride-sharing. Following the principle of FCFS, we give precedence to the longest-waiting traveler. However, we allow other passengers to enter the SAV if they are traveling to the same, or a close destination. Specifically, suppose that the SAV $v \in V$ is initially empty, and the longest-waiting traveler at $i \in Z$ is $d_0$, seeking to travel from $i$ to $j \in Z$. If there is another traveler $d_1$ also seeking to travel from $i$ to $j$, then $d_1$ may take the same SAV. If there is a traveler $d_2$ seeking to travel from $i$ to $k \in Z$, and there is room in the SAV, $d_2$ may also take the same SAV if the additional travel time is sufficiently low. Let $t_{ij}$ be the expected travel time from $i$ to $j$. Then $d_2$ will take the SAV if $t_{ij} + t_{jk} \leq (1 + s)t_{ik}$. Otherwise, $d_2$ will wait at $i$. If $d_2$decides to take the SAV, then any other waiting travelers at $i$ also traveling from $i$ to $k$ may enter the SAV. Although this violates FCFS, this is permitted because it does not impose any additional travel time on the SAV.

This offer is extended, in FCFS order, for all travelers waiting at $i$ until $v$ is full. For instance, suppose a passenger $d_3$ departing after $d_2$ is traveling from $i$ to $l \in Z$. Because of FCFS, $v$ must service $d_2$first, but if $t_{ij} + t_{jk} + t_{kl} \leq (1 + s)t_{il}$, then $d_3$will still take SAV $v$ from $i$.

The logic is slightly different when $v$ arrives at $i$ already carrying a passenger. In that case, precedence is given to all passengers already in $v$ because they have been traveling. However, travelers in $i$ may enter $v$ — at the back of the queue — if the additional travel time is less than $s$ of the direct travel time.

The problem of dynamic ride-sharing is a vehicle routing problem with all SAVs. In general, vehicle routing problems can admit solutions in which an SAV picks up several passengers before dropping any off. The heuristic in this case study does not do that due to complexity, although that behavior could certainly be implemented within this framework. In practice, due to the necessity of tractability when solving vehicle routing problems in real-time in response to demand, similar simple heuristics are likely to be used. Even with this restricted form of dynamic ride-sharing, the benefits over non-ride-sharing SAVs are significant, as shown below.

*Preemptive Relocation*

Preemptive relocation can reduce waiting times by starting to move SAVs to travelers' locations before they depart. Fagnant & Kockelman (2015) studied four strategies for preemptive relocation and found that the best performing heuristic distributed SAVs to each centroid according to the proportion of productions. Since productions are typically determined by a survey of land use, the total expected trip productions at any centroid is likely to be known even if specific traveler departure times are not. Formally, let $\mathcal{P}_i$be the productions and $V_i$ the set of SAVs parked at $i \in Z$.

The number of SAVs to be moved to $i$ is

$$\Delta V_i = \frac{|V_i|}{|V|} - \frac{\mathcal{P}_i}{\sum_{i' \in Z} \mathcal{P}_{i'}}$$

If $\Delta V_i > 0$, $\Delta V_i$ SAVs are moved from $i$; if $\Delta V_i > 0$, $-\Delta V_i$ SAVs are moved to $i$. Let $\mathcal{Z}^+ = \{i \in Z | \Delta V_i > 0\}$ and $\mathcal{Z}^- = \{i \in Z | \Delta V_i > 0\}$. $\mathcal{Z}^+$ is sorted in decreasing order. For each $i \in \mathcal{Z}^+$, $\Delta V_i$ SAVs from $i$ are distributed to the nearest centroids (by travel time) in $\mathcal{Z}^-$. This attempts to minimize the congestion caused by relocation.

### 4.4.3 Summary

This section presented an event-based framework for implementing SAV behavior in existing traffic simulation models. The framework relies on two events: travelers calling SAVs, and SAVs arriving at centroids, that are orthogonal to traffic flow models. This allows comparisons with personal vehicle scenarios through solving traffic assignment in the same simulator. We implemented this SAV framework within a cell transmission model-based dynamic traffic assignment simulator as well as heuristic approaches to preemptive relocation and dynamic ride-sharing.

### 4.4.4 Shared Autonomous Vehicle (SAV) Simulation Results

Many sets of experiments were undertaken to study how SAVs perform relative to personal vehicles, and how preemptive relocation and dynamic ride-sharing affect performance. Experiments were performed primarily on the downtown Austin network. This is only a subnetwork of the larger Austin region, which has 1.2 million trips. This subnetwork was used because computation times were around 30–40 seconds per scenario on an Intel Xeon running at 3.33 GHz (with the SAV framework and CTM implemented in Java), allowing many scenarios to be studied. However, many trips bound for the downtown grid originate from outside the subnetwork region. They were approximated as arriving from one of the subnetwork boundaries. The data was provided by the Capital Area Metropolitan Planning Organization.

Initially, SAVs were distributed proportionally to zones based on the number of productions in each zone. The assumption is that all SAVs could be relocated overnight to fulfill these proportions at the start of the AM peak This reallocation is different than preemptive relocation which is relocating SAVs during the AM peak, while travelers are requesting SAVs. Fagnant & Kockelman (2014) used a seeding run to determine the number of SAVs necessary to service all travelers. Instead of a seeding run, a sensitivity analysis was performed to study how increasing numbers of SAVs affected travel time. A seeding run may have biased the number of SAVs to be lower. In some scenarios (such as dynamic ride-sharing) it was observed that lower numbers of SAVs performed better due to lower congestion. However, in other scenarios, higher numbers of SAVs improved service. The following charts contain experiments using between 4,000 and 40,000 SAVs, with increments of 500. For some scenarios, the range was reduced to the number of SAVs that could provide service to all travelers within 6 hours, because service was limited by having too few SAVs or too much congestion.

*Personal Vehicles*

First, to create a base scenario, DTA was solved on downtown Austin, assuming that all travelers use privately owned CAVs for their trips. Although SAVs use a dynamic network loading-style route choice, the DTA model assumed drivers based their routes on past experience to find a dynamic user equilibrium. Therefore, the routing strategy in DTA is likely more efficient than the routing strategy for SAVs. Overall, when using personal vehicles with traffic signals, travelers experienced an average travel time of 15 minutes. When signals were replaced with reservation controls, average travel times were reduced to 7 minutes. Since the adoption of reservation controls may be difficult or inefficient if a significant proportion of personal vehicles are not autonomous, both DTA scenarios may be reasonable for comparison against SAVs. The assumption made here was that if SAVs were to replace all personal vehicles, reservation controls would be used.

*Shared Autonomous Vehicles*

The initial SAV scenario did not include preemptive relocation or dynamic ride-sharing. Figure 4.19 shows travel time results with 28,500 to 40,000 total SAVs available. (Lower numbers of SAVs were found to be insufficient to service all travelers after 6 hours.) As the number of SAVs increased, waiting time decreased linearly. Vehicle miles traveled (VMT) and empty VMT—miles traveled while not carrying any passengers—decreased at the same rate as the number of SAVs increased (Figure 4.19). This indicates that the difference was primarily due to fewer repositioning trips to pick up the next traveler. It is intuitive that as the number of SAVs increased, the average distance between a waiting traveler and the closest available SAV would decrease. Overall travel times in this base SAV scenario were much higher than with personal vehicles. In-vehicle travel time, interestingly, decreased for around 31,000 to 32,000 SAVs, then remained nearly constant thereafter. This may be due to a reduction in congestion when SAVs were traveling less for repositioning trips. In-vehicle travel times of 33–35 minutes, however, are double that of DTA with signals , and five times that of DTA with CAVs. Previous studies predicted that each SAV can service multiple travelers with acceptable waiting times—that is still true in these experiments, but the travel times experienced are more similar to those of public transit. Travelers may be unwilling to use SAVs if the travel times are this high.

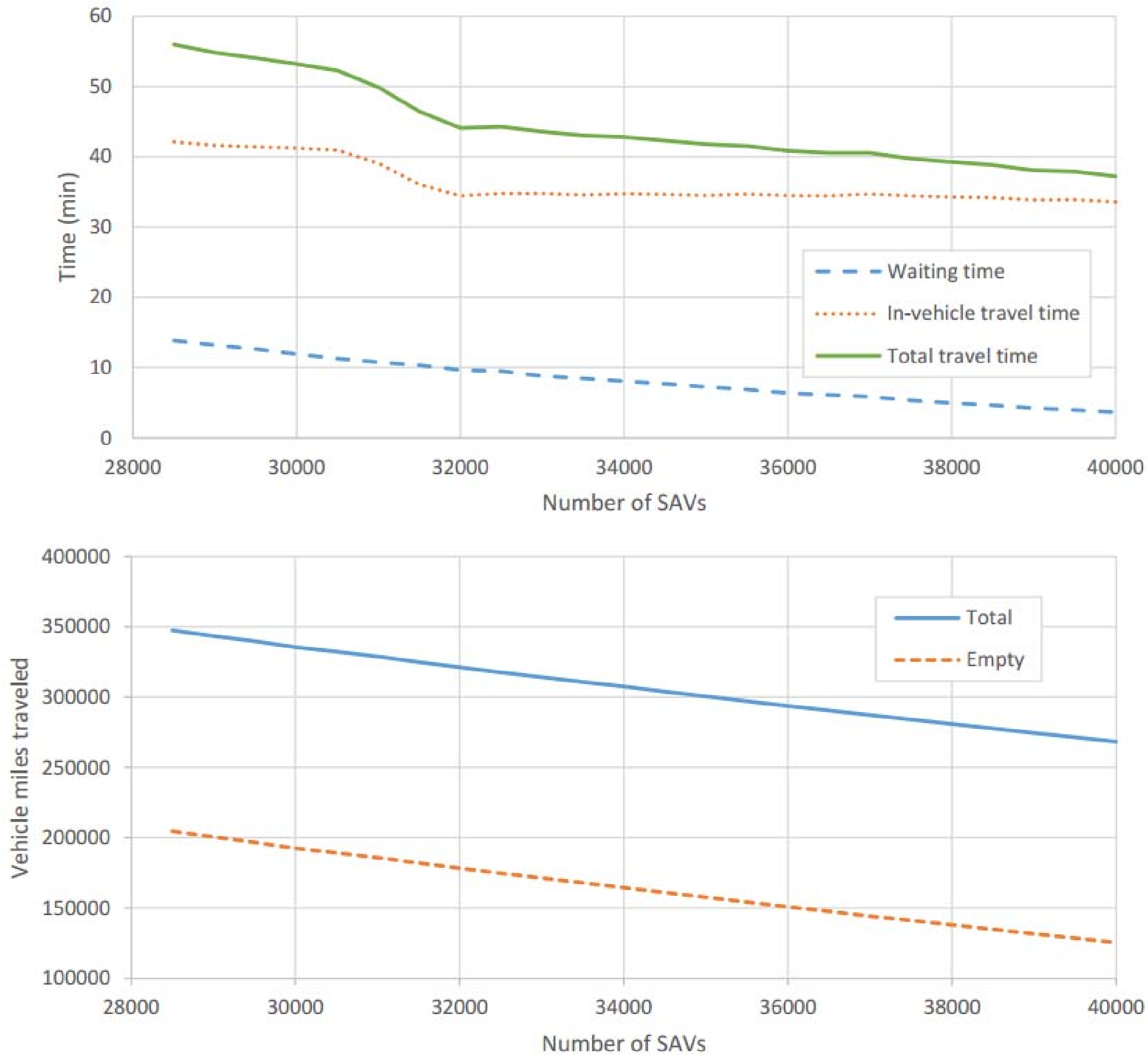



*Figure 4.19: Travel Time and VMT for the Base SAV Scenario*

The difference in travel time is most likely due to additional congestion from empty repositioning trips made to pick up the next traveler. The downtown Austin network is already fairly congested during the AM peak, and the addition of repositioning trips makes matters worse. This is an important result, however, because it demonstrates the value in using a realistic traffic flow model for analyzing congestion. For less congested networks, SAVs might cause only modest increases in congestion. However, for a high-traffic city in the AM peak, these results are not encouraging for a switch to SAVs.

*Preemptive Relocation*

Next, the effects of preemptively relocating SAVs to match the proportion of productions of each centroid was studied. This resulted in very high waiting times with few SAVs available. This is likely due to the fairness of assigning SAVs: travelers are prioritized by the time spent waiting. Unless a traveler was waiting at the destination of the relocating SAV, it would be re-assigned to service a different traveler, which is likely why the waiting time was so high when few SAVs were available. Although this is a reasonable policy, alternatives such as that of Fagnant and Kockelman (2014), in which travelers are prioritized according to distance from the available SAV, could improve average waiting time.

As the number of SAVs increased, waiting time decreased linearly, although it was still much higher than the base scenario. One potential reason is the additional congestion resulting from relocating SAVs. This is illustrated by the much higher empty VMT resulting from relocations, shown in Figure 4.20. Relocating resulted in around 400,000 vehicle miles of empty travel. This did not decrease as the number of SAVs increased, as it did in the base scenario, which likely contributed to the increasing in-vehicle travel times. The in-vehicle travel time increased linearly with the number of SAVs, which is indicative of those additional SAVs contributing significantly to congestion. In fact, beyond 20,500 SAVs, congestion prevented effective service for all travelers. Although waiting time decreased, the increases in travel time resulted in only small decreases in TTT.

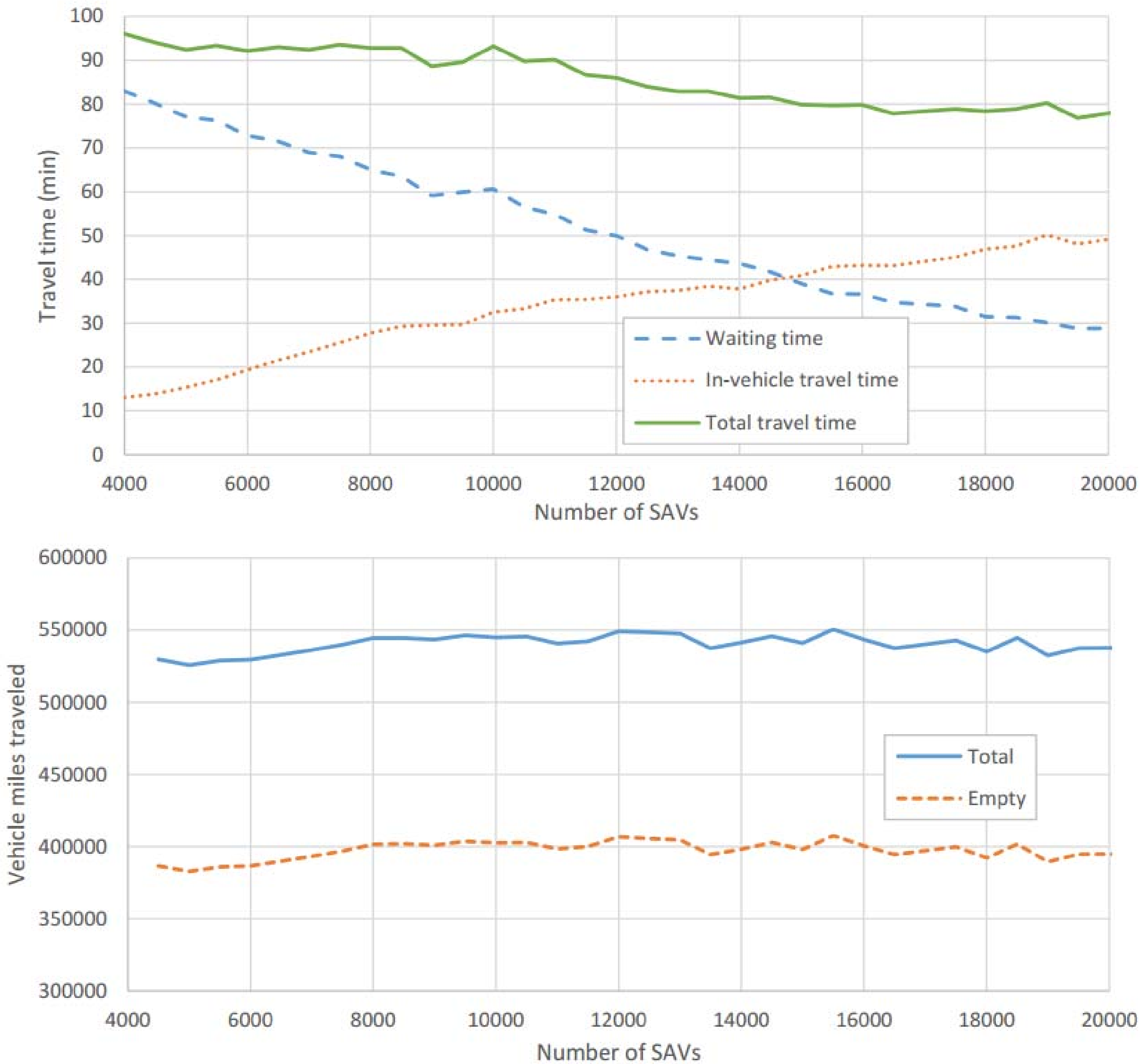



*Figure 4.20: Travel Time and VMT for the Preemptive Relocation Scenario*

*Dynamic Ride-Sharing*

Compared with the base and pre-emptive relocation SAV scenarios, dynamic ride-sharing allowed SAVs to provide in-vehicle travel times competitive with personal vehicles. SAV capacity was four passengers, and $\epsilon$ was set at 0.4 (Fagnant and Kockelman 2015). At the minimum scenario of 4000 SAVs, the average in-vehicle travel time was 12.4 minutes and the average waiting time was only 5.1 minutes, as shown in Figure 4.21. For travelers who call a SAV a few minutes before they plan to leave, a 5.1-minute waiting time is easily forgivable. Those 12.4-minute in-vehicle travel times improve over average travel times with personal vehicles and traffic signals, and are only around 5 minutes greater than personal vehicles with reservation controls. As the number of SAVs increased, though, travel times also increased until they were comparable with the non-ride-sharing scenario. Waiting times were overall much lower. This was probably because travelers with nearby destinations could share the same SAV, when one arrived. This approach yielded the best results when the fewest SAVs were available: despite increased waiting times, SAV utilization was greater.

Figure 4.21 shows that VMT peaked with around 23,000 SAVs. With only 4000 SAVs, VMT was low because of the low number of SAVs, but dynamic ride-sharing allowed just 4000 SAVs to service 62,836 travelers in the AM peak. Note that the difference between total and empty VMT increases as the number of SAVs increases due to the reduction in average number of passengers carried per SAV. This demonstrates an interesting result: when ride-sharing is possible, having fewer SAVs is sometimes more efficient. Ride-sharing reduces congestion and maximizes the utilization of each SAV because travelers accumulate as they wait for one of the few SAVs to arrive for pick-up

A fleet of 4000 SAVs corresponds to a 93.6% reduction in the number of vehicles: each SAV services an average of 15.7 travelers. This efficiency is similar to that found in previous studies, such as one SAV servicing 11 travelers (Fagnant and Kockelman 2014). However, the observed efficiency is at least partially due to the network topology: due to considering only the downtown region, traveler origin/destinations are fairly close together. If a regional network were used, the efficiency would likely decrease.

Preemptive relocation was somewhat detrimental when used with dynamic ride-sharing, as shown in Figure 4.22. When the number of SAVs was below 10,000, preemptive relocation slightly reduced waiting times. At higher numbers of SAVs, though, relocation still had a waiting time of around 3–4 minutes. This probably resulted from high congestion delaying the arrival of relocating vehicles. Beyond 20,000 SAVs, the congestion caused by the additional relocations prevented travelers from reaching their destination. Travel time increased significantly with the number of SAVs, mostly due to increases in in-vehicle travel time from congestion. However, travel time with ride-sharing and relocation increased at a lower rate than travel time with just ride-sharing. In fact, when the number of SAVs was between 4000 or 10,000, preemptive relocation with ride-sharing had slightly lower travel times than ride-sharing alone. However, at higher numbers of SAVs, with ride-sharing available, most SAVs were relocating, resulting in high congestion and worse travel times than in the base case. As the number of SAVs increased, the empty VMT increased as well, resulting in around 100,000 additional miles traveled at 20,000 SAVs when relocation and ride-sharing was used compared to ride-sharing alone (Figure 4.22).

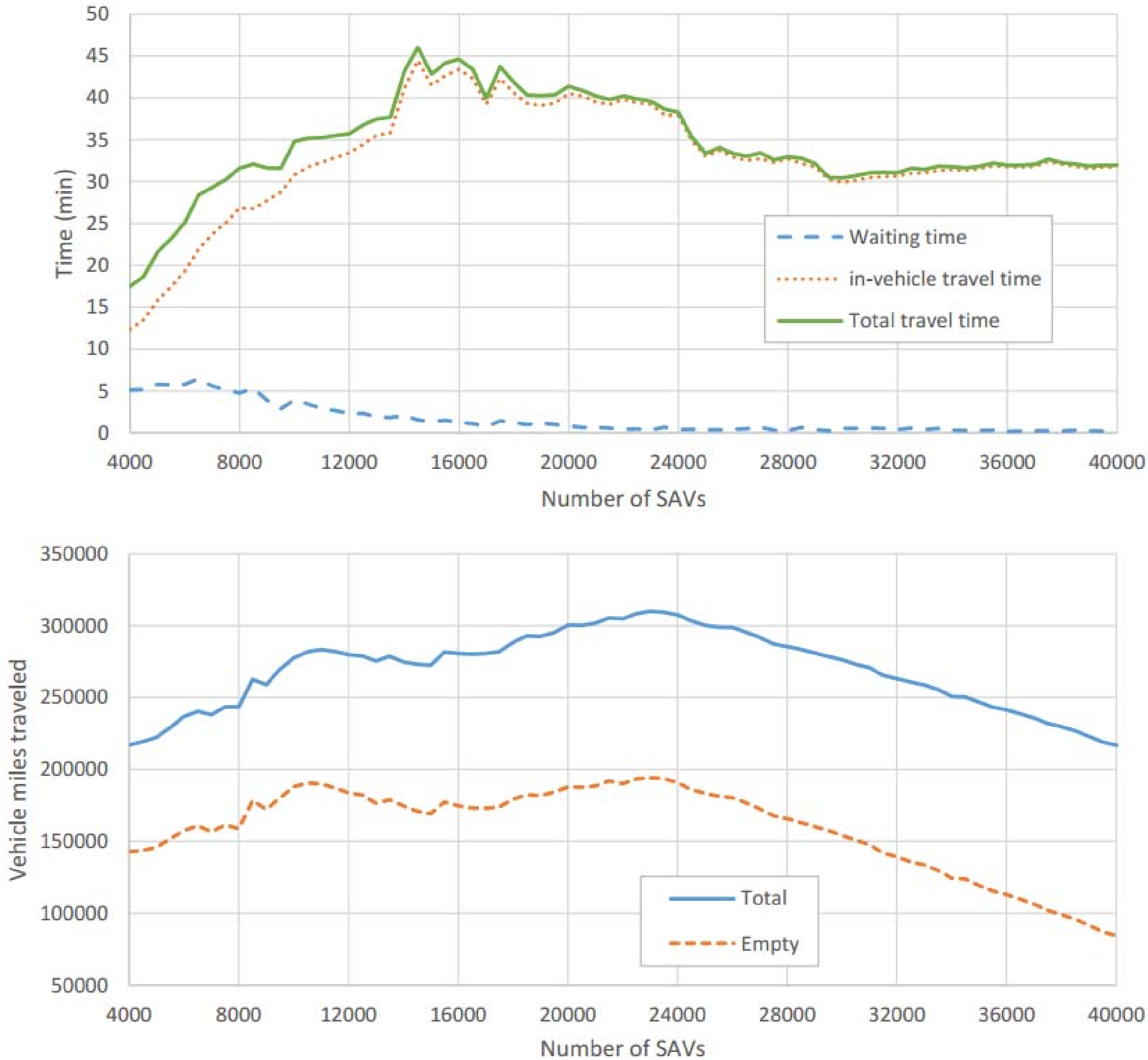
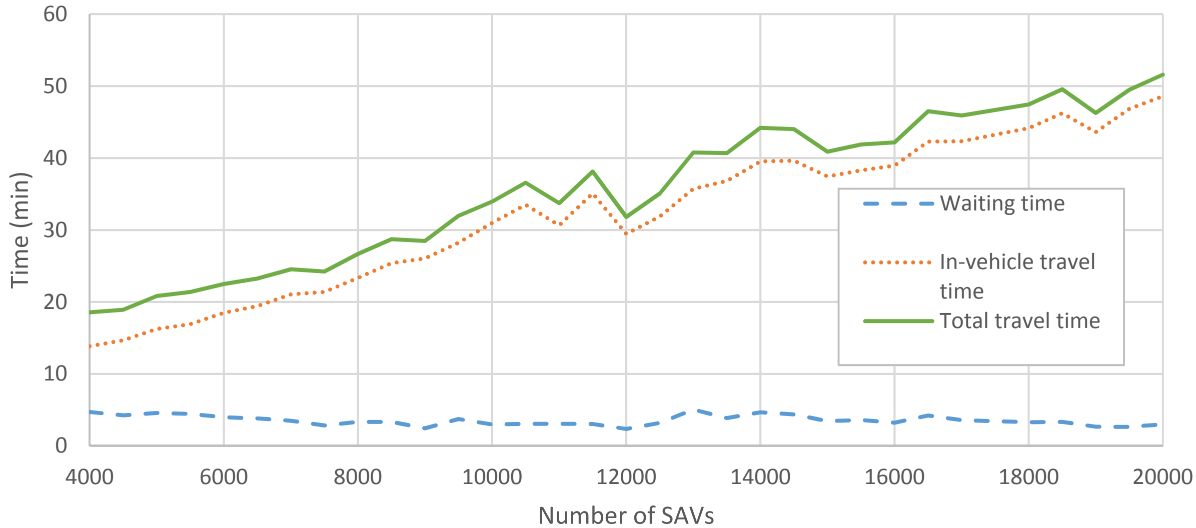



*Figure 4.21: Travel Time and VMT for the Dynamic Ride-Sharing Scenario*



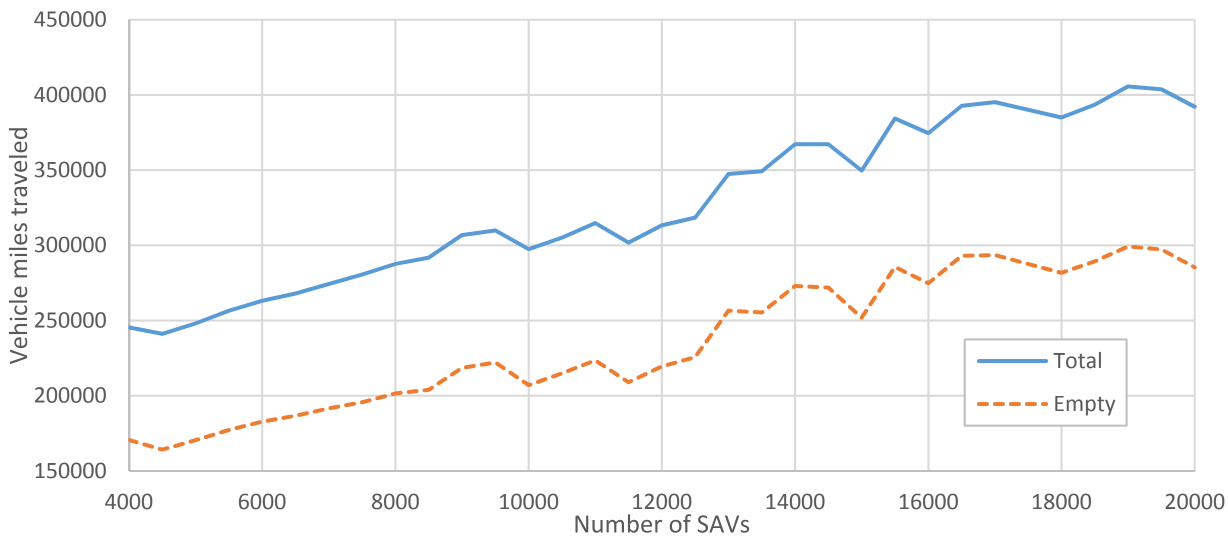




*Figure 4.22: Travel Time and VMT for the Dynamic Ride-Sharing and Preemptive Relocation Scenario*

# Chapter 5. Benefit/Cost Analysis

In order to assess potential benefits to the transportation system and its users stemming from CAVs, it is first critical to assess the existing scope of problems faced by the traveling public. To these ends, this report attempts to quantify these problems across two major domains: congestion and crashes. During the course of the project, the team developed initial estimates, which were then refined using the results of the other analyses performed. Section 5.1 describes the preliminary estimates generated towards the start of the project, and Section 5.2 the updated estimates generated near the end.

## 5.1 Preliminary Estimates

### 5.1.1 Congestion

Congestion exists as a consistent economic drain on the state. While Texas is in an enviable position compared to many other parts of the nation, given its growing economy and relatively plentiful jobs, it remains important to protect the state's advantage as a lower-cost, business-friendly location by avoiding scenarios where increasing congestion imposes costs harmful to the state's economy. Based on the 2015 Urban Mobility Report (Schrank et al. 2015), urban areas of all sizes are experiencing the challenges related to increasing levels of congestion. Data from 1982 to 2014 show how congestion has expanded over time on a national level, and may continue to increase (absent systemic changes), as shown in Table 5.1.

**Table 5.1: Major Findings of the 2015 Urban Mobility Scorecard (471 U.S. Urban Areas)**

| U.S. Congestion Costs | 1982 | 2000 | 2010 | 2013 | 2014 |
|---|---|---|---|---|---|
| Travel delay (billion hours) | 1.8 | 5.2 | 6.4 | 6.8 | 6.9 |
| Wasted fuel (billion gallons) | 0.5 | 2.1 | 2.5 | 3.1 | 3.1 |
| Congestion cost (billions of 2014 dollars) | $42 | $114 | $149 | $156 | $160 |

While these dramatic changes are occurring nationwide, Texas' population growth continues to outpace the rest of the country, and thus the state is experiencing significant congestion strains. Table 5.2 summarizes the extent of Texas' road congestion problems, as measured across multiple performance measures for the state's major urban areas[13] in 2014.

[13] Defined as the developed area (population density more than 1,000 persons per square mile) within a metropolitan region.

**Table 5.2: Congestion Data for Texas Urban Areas**

(Sources: TTI 2014 & Schrank et al., 2015)

| | **Austin** | **Dallas-Fort Worth** | **Houston** | **San Antonio** | **Others**[14] | **National level** |
|---|---|---|---|---|---|---|
| **Population (1000 s)** | 1,500 | 5485 | 5000 | 1935 | 2600 | -- |
| **Daily Vehicle-Miles of Travel (1000s)** | | | | | | |
| Freeway | 13,273 | 64,411 | 51,673 | 21,270 | 15,755 | -- |
| Arterial streets | 11,237 | 41,713 | 39,211 | 12,956 | 20,746 | -- |
| **Annual Excess Fuel Consumed** | | | | | | |
| Total Fuel (1000 gallons) | 21,654 | 79,392 | 94,300 | 28,809 | 28,431 | -- |
| Fuel per Peak Auto Commuter (gallons) | 22 | 22 | 29 | 20 | 14 | 19 |
| **Annual Delay** | | | | | | |
| Total Delay (1000s of person-hours) | 51,116 | 186,535 | 203,173 | 64,328 | 58,823 | -- |
| Total Delay (Freeway)[15] | 19,936 | 72,748 | 79,237 | 25,088 | 9,411 | -- |
| Total Delay (Arterials) | 31,180 | 113,786 | 123,935 | 39,240 | 49,411 | -- |
| Delay per Peak Auto Commuter (person-hrs) | 52 | 53 | 61 | 44 | 29 | 42 |
| **Travel Time Index** | 1.33 | 1.27 | 1.33 | 1.25 | 1.15 | 1.22 |
| **Freeway Planning Time Index (95th Percentile)** | 2.58 | 2.65 | 3.13 | 2.12 | 1.6 | 2.41 |
| **Congestion Cost (constant 2014 $)** | | | | | | |
| Total Cost ($ millions) | $1,140 | $4,202 | $4,924 | $1,462 | $1,351 | -- |
| Cost per Peak Auto Commuter ($) | $1,159 | $1,185 | $1,490 | $1,002 | $676 | $960 |

When taken collectively, these measures show that Texans annually experience over 560 million hours of delay, going relatively slowly or sitting in traffic, with an economic cost of over $13 billion. As should be expected, higher levels of VMT, total fuel consumption, delays, and congestion costs are seen in Texas' larger cities. On a per-commuter basis, Houston travelers experience the greatest congestion costs, followed by those from Dallas-Fort Worth and Austin. While not quantified in terms of direct economic costs, the travel time variability measures (travel time index and freeway planning time index) represent real costs to travelers as well, since travelers must either leave increasingly early or risk being late. In sum, this data clearly illustrates the scope of congestion impacts to Texas in terms of wasted time and lost economic efficiency.

Furthermore, historical data shown in Figure 5.1 illustrates growing population trends along with several congestion performance measures in recent years from 2010 to 2014 (TTI 2014). These charts show how congestion continues to worsen across the state with continued population growth and economic activity.

[14] These include El Paso, Laredo, McAllen, Brownsville, Corpus Christi, and Beaumont, Texas. Values per peak-period automobile traveler were calculated using a weighted average by population as weights.

[15] These values were calculated using the base share of delay on freeways vs. arterials at the national level provided by (Schrank et al., 2015), and adjusted based on freeway vs. arterial VMT differences when comparing Texas to U.S. averages.

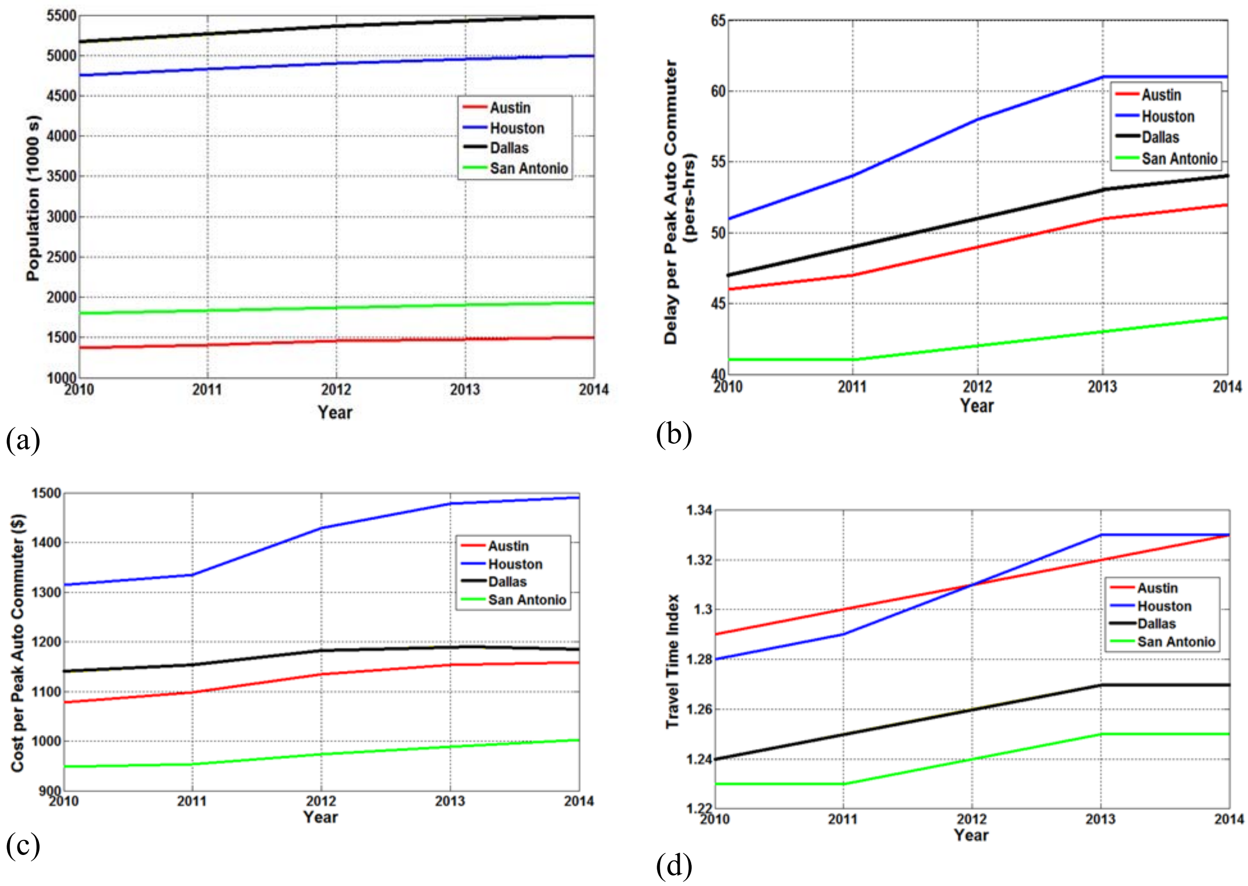



*Figure 5.1: Trends of (a) Population, (b) Delay, (c) Cost and (d) Travel Time Index per Peak Auto Commuter from 2010 to 2014.*

The congestion problem can be further broken down into its component parts based, on roadway type. Nationally, more delay is experienced on surface streets than freeways, and larger urban areas experience higher shares of their delay on freeways than in smaller cities. Additionally, approximately 40% of delay occurs in off-peak hours, as shown in Figure 5.2, indicating a persistent problem that could be potentially ameliorated with carefully considered CAV strategies.

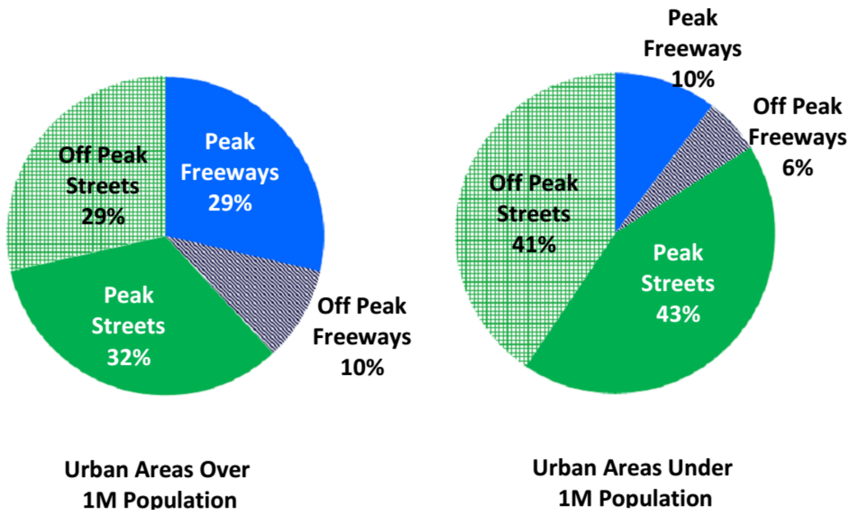



*Figure 5.2: Percent of Delay, By Road Type and Time of Day*

While the Urban Mobility Report outlines the total impacts of congestion costs in urban areas, there may be opportunities for some mobility enhancements in rural areas and small towns too. For example, a small town may have 20 traffic signals, each with 2,500 entering vehicles during the highest traffic hour. If 10 seconds of delay could be shaved off each signal through cooperation with CAVs, over a half million hours of delay could be saved per year. Though this figure pales in comparison to the delay experienced in Texas' major cities, the cumulative impacts across Texas' numerous small towns could become sizable. Since the scope of delay and potential for improvement in small towns has not been quantified in the literature, this chapter cannot adequately quantify these potential impacts with any accuracy. Therefore, readers should note that the true potential for delay reductions could be greater than estimated in this report, due to the omission of potential improvements in small towns outside of large urban metro areas.

### 5.1.2 Crashes

In 2013 Texas experienced more than 446,000 crashes, resulting in 3,065 fatalities and over 296,000 injuries (TxDOT 2014). With nearly 250 billion VMT per year, this translates to one crash for every 532,000 VMT and one fatality for every 78 million VMT. This comes at a total comprehensive economic cost of $83 billion (or $3,000 per Texan per year), a tremendous social burden. While most collisions occurred in urban areas (75.2% of all crashes), fatalities in rural areas were typically more severe, accounting for 55.4% of all fatalities. Table 5.3 outlines crash count distributions, by severity and setting, across the state.

**Table 5.3: Number of Crashes in Texas, 2013**

| Crashes | # Crashes | | | # Injuries | | |
|---|---|---|---|---|---|---|
| | Rural | Urban | Statewide | Rural | Urban | Statewide |
| # of Fatal Crashes or Fatalities | 1,648 | 1,417 | 3,065 | 1,887 | 1,521 | 3,408 |
| # Incapacitating Crashes or Injuries | 5,184 | 8,254 | 13,438 | 6,847 | 9,960 | 16,807 |
| # Non-Incapacitating Crashes or Injuries | 13,778 | 38,433 | 52,211 | 20,205 | 52,430 | 72,635 |
| # Possible Injury Crashes or Injuries | 16,218 | 72,591 | 88,809 | 26,236 | 116,921 | 143,157 |
| # Non-Injury Crashes or Non-Injuries | 70,655 | 201,946 | 272,601 | 203,259 | 694,664 | 897,923 |
| # Unknown Severity Crashes or Injuries | 2,950 | 12,755 | 15,705 | 8,539 | 51,766 | 60,305 |
| *Total Number of Crashes or Injuries* | *110,433* | *335,396* | *445,829* | *63,714* | *232,598* | *296,312* |

Rural and urban settings have their own unique characteristics in terms of traffic flow, roadway facilities types, traffic control, operating speeds, and other factors. These characteristics also lead to differences in incidence rates. For example, NHTSA (2015) estimates a fatality rate per 100 million VMT in rural areas at 1.88 compared to just 0.73 for urban areas.

In addition to context, motorcycle crashes are of particular concern to CAVs. Collisions that a CAV can avoid in these instances are inherently limited, since a CAV can only prevent its own mistakes, and not those of a motorcyclist. And while a motorcycle can be automated (see e.g., Brassfield 2014), the appeal of a self-operating motorcycle seems quite limited. With approximately half of all motorcycle fatalities being single-vehicle collisions (Fagnant and Kockelman 2015), this share of crashes is assumed to remain unchanged.

Moreover, motorcycle crashes are often quite severe. While motorcycle-involved crashes represented just 0.8% of all collisions in Texas, they accounted for over 15% of statewide fatalities. This means motorcyclists are more vulnerable in the event of a crash, with associated higher likelihood of a fatality resulting, and along with higher expected crash cost per motorcycle. The number of motorcycle injuries is shown in Table 5.4.

**Table 5.4: Motorcyclist Injuries in Texas, 2013**

| Types of Injuries | Motorcyclist Injuries | All Crash Injuries | Motorcyclists' Injury Share |
|---|---|---|---|
| Fatalities | 503 | 3,408 | 14.8% |
| Incapacitating Injuries | 1,969 | 16,807 | 11.7% |
| Non- Incapacitating Injuries | 3,698 | 72,635 | 5.1% |
| Possible Injuries | 2,002 | 143,157 | 1.4% |
| Non-Injuries | 1,283 | 897,923 | 0.1% |
| Unknown Injuries | 184 | 60,305 | 0.3% |
| *Total TX Motorcycling Injuries* | *8,356* | *29,312* | *0.8%* |

Crash injury severities were then translated from the KABCO scale to the MAIS scale, using Blincoe et al.'s (2015) estimates, in order to calculate total economic and comprehensive crash costs. In addition to economic components such property damage, delay, medical costs, lost productivity, and other factors, comprehensive crash costs also include external measures such as quality-adjusted life years and willingness-to-pay measures for avoiding crashes. Table 5.5 depicts the estimated number of injuries in Texas across the MAIS severity scale, along with per-crash economic and comprehensive valuations associated with each severity level.

**Table 5.5: Number of Injured Persons in Crashes and Costs per Injured Person**

| Severity | # Injured Persons (all Injuries) | # Injured Motorcyclists | Economic Cost/Injury | Comprehensive Cost/Injury |
|---|---|---|---|---|
| Fatal | 3,408 | 532 | $1,398,916 | $9,145,998 |
| MAIS5 | 1,213 | 55 | $1,001,089 | $5,579,614 |
| MAIS4 | 1,910 | 86 | $394,608 | $2,432,091 |
| MAIS3 | 9,181 | 867 | $181,927 | $987,624 |
| MAIS2 | 32,015 | 1,511 | $55,741 | $396,613 |
| MAIS1 | 358,219 | 5,240 | $17,810 | $41,051 |
| MAIS0 | 788,080 | 1,348 | $2,843 | $2,843 |

These valuations indicate that the total economic cost of Texas' 446,000 crashes in 2013 exceeded $19 billion, rising to $83 billion once comprehensive costs are included.

It should be noted that this is markedly higher than TxDOT's 2013 crash cost estimate of $27.8 billion, since TxDOT's figures rely on the National Safety Council's valuations (NSC 2012), which include economic components only, and are somewhat less current and rigorous than Blincoe et al.'s (2015) work.

### 5.1.3 Implications for Travel and Vehicle Ownership

As CAVs become more prevalent, they are bound to impact our interface with the transportation system. Texas may see an increase in VMT as commuters take their self-driving vehicles to work, then send them home to park for free or be used by other family members. Trip generation may rise as those previously unable to drive (e.g., children, the elderly, and disabled persons) achieve newfound independent mobility. Empty vehicles may drive themselves from one location to another, to park less expensively or serve the travel needs of another person. Airlines may see fewer passengers as more long-distance travelers take to the roadways (LaMondia et al. 2016). Ultimately, people may choose different destinations and home and work and school locations, as motorized travel becomes less onerous.

Household vehicle ownership patterns may also change. As fleets of shared on-demand driverless vehicles become available (also known as shared autonomous vehicles, or SAVs), households may choose to own fewer cars, relying on SAV services instead for some or even all of their travel needs. This section examines potential impacts across both VMT and vehicle ownership dimensions, in order to predict potential changes that Texas may experience, and the resulting impacts on congestion and safety.

*Vehicle-Miles Traveled (VMT)*

With the arrival of CAVs, it is quite likely that we will see a net increase in total VMT. Individual travelers will be freed, enabling them to read a book, use a laptop, relax, or perform other activities previously not possible to undertake while driving (at least safely). This should lead to an effective reduction in the perceived values of travel time (or alternatively, travel time burdens) for CAV users. Indeed, Gucwa (2014) estimated a potential 4–8% VMT increase due to lower perceived values of travel time and increased road capacity, due to CAV capabilities. Additionally, once fully automated vehicles arrive, CAVs may afford new mobility opportunities for those currently unable to drive. This development may also give rise to a new transport mode, the shared AV (SAV). SAVs may act as on-demand driverless shuttles or taxis, transporting travelers from one location to the next throughout the day. It is highly probable that some of this travel will be unoccupied at times, thus introducing new VMT, though if enough ridesharing takes place, net reductions could possibly result. Fagnant and Kockelman (2015) estimated that, when serving 1.3% of regional trips by SAV (with no ridesharing), total VMT rose by 8.7% on a per-trip basis. However, when ridesharing was incorporated into the model, just 4.5% VMT was added, and this figure could be pushed to below zero (i.e., VMT reductions) with greater SAV demand or looser ridesharing parameters. Moreover, (if not prohibited) it may also be possible for individual CAV owners to send their vehicles to cheaper parking locations, thus creating even more VMT.

When considering all of these factors together, several assumptions may be made in order to develop an order-of-magnitude estimate for the potential changes in VMT at various levels of market penetration. At the 10% market penetration level, a 20% VMT increase is assumed per CAV, to account for latent demand (i.e., those previously unable to drive) as well as falling values of travel time, and unoccupied CAV travel. Added VMT per CAV is assumed to fall to 15% at the 10% market penetration level (i.e., CAVs between the 10–50% range will see 15% per-CAV travel increases, on top of the 20% increases shown by the first 10% of CAV adopters), and just 10% at the 90% market penetration level. These falling values account for the increased potential for ridesharing via SAV (and less unoccupied relocation), as well as the fact that latent demand from those unable to drive would already have been served. Since there is likely greater utility for unoccupied travel in urban areas (e.g., due to avoiding pricy parking and unoccupied travel by SAVs), rural areas are assumed to experience half of the per-CAV travel as that seen in urban areas. These per-AV increased travel values are consistent with prior estimates conducted by Fagnant and Kockelman (2015).

This noted, additional VMT is estimated here, beyond estimates conducted in Fagnant and Kockelman's (2015) work, for other travelers who are not CAV users. CAVs should improve operational efficiencies through freeway traffic flow harmonization and smoothing, platooning via CACC, and an anticipated reduced collision rate. All of this should create an effective increase in capacity, leading to reduced travel times across all travelers. As capacity increases and traffic delays fall, prior studies show, utilization increases on those same facilities. For example, Cervero's (2001) review of literature for cities in California and the U.S. across 30 years found that urban demand elasticity with respect to highway lane miles averaged 0.74. This implies that a 1% increase in a region's total lane miles should correspond to a 0.74% increase in VMT.

It is unlikely that the full magnitude of the 0.74 average elasticity found by Cervero will materialize due to effective capacity increases enabled via CAVs. In the past, roadway construction improvements were targeted to address specific needs, while CAV capabilities may have broad-based effects, regardless of whether any latent travel demand is present, or would otherwise materialize absent capacity increase. Therefore, a demand elasticity of non-CAVs with respect to capacity increase is assumed to be 0.40 at the 10% market penetration level. As with CAVs, the incremental impacts of added capacity is assumed to fall with greater market penetration (and thus greater effective capacity increases), and therefore elasticity values are assumed to fall to 0.20 and then just 0.10 at the 50% and 90% market penetration levels, respectively. Since congestion is a minimal factor if present at all in rural areas, no rural VMT increases due to latent demand factors are assumed in this analysis.

*Vehicle Ownership*

As CAVs enter the market, eventually the requirement for a driver to be present will fall, giving rise to SAVs. The value proposition inherent in SAVs is quite substantial—instead of owning your own vehicle, simply summon an on-demand SAV via smartphone when you need one, and share a ride if you wish to save some money and someone else is headed in the same direction. Indeed, in many ways this is a similar framework to what transportation network companies (TNCs) currently operate. Uber has publicly stated its intention of transitioning to SAVs as they become feasible (Harris 2015), and Google has similar plans with its recently introduced fleet of SAV prototypes. Yet SAVs have many advantages beyond current TNC models with human drivers. System-optimal vehicle fleet control will be possible (rather than relying on drivers to make decisions of when and where to operate that impact the entire fleet), SAVs do not need to take breaks and can work around the clock, and most importantly, cost savings may be dramatic. To this last point, Fagnant and Kockelman's (2015) simulations estimated that a fleet of 2118 SAVs serving 1.3% of Austin regional trips could cut equivalent taxi fares from around \$3 per mile to just \$1 per mile, while still garnering an annual return on investment capital of nearly 20% per year. Moreover, this assumes a vehicle purchase price of \$70,000, and long-term market projections for the cost of added vehicle automation is anticipated to be around \$10,000 or less (Fagnant and Kockelman 2013).

Consequently, it is highly likely that a significant share of households will come to rely on SAVs for their travel needs, and shed one or more personally owned vehicles. This will likely occur most frequently in more densely populated areas, since SAVs are most effective with increased trip intensity and high parking costs. The question then remains as to how large of a market share SAVs will comprise, as a proportion of all CAVs. It is possible that they will come to dominate the market (as projected by Zachariah et al. 2014), or alternatively comprise just a small part of the transportation ecosystem, perhaps just above current TNC and taxi shares. Both scenarios are certainly plausible, with economic efficiencies driving the first vision; and an implicit value of ownership, locked mobile storage, and vehicle availability certainty driving the second. Instead, here it is anticipated that SAVs will displace less-intensely used vehicles in urban areas, thus comprising a large but not overwhelming share of CAVs. Thus, this report projects roughly half of all CAV trips will be served by SAVs, consistent with Fagnant and Kockelman's (2015) prior estimates.

### 5.1.4 Mobility

*Potential Mobility Impacts of Connected & Automated Vehicles*

The potential benefits for enhanced mobility are also quite substantial. CAVs have the potential to increase effective road capacity and efficiency through reducing vehicle headways when platooning, operating more efficiently with traffic signals, utilizing intelligent merging with automated on-ramp metering, and harmonizing speeds to smooth traffic flow. On arterials and other surface streets, additional efficiencies may be gained through intelligent coordination with signals. Additionally, with fewer crashes anticipated due to safety improvements, non-recurring congestion stemming from crashes should fall. The FHWA (2005) estimates that around 25% of urban congestion is due to non-recurring events, around half of which is attributed to collisions.

CACC is one emerging technological application with the potential for significantly enhancing roadway efficiency. CACC aims to reduce gaps between communicating CAVs, facilitating the creation of tightly spaced vehicle platoons, with gaps between vehicles as low as just several meters. CACC utilizes V2V communication in combination with vehicle automation to form these platoons. V2V communication enables the precise transmission (10 times per second) of location, velocity, gap, and any acceleration or braking actions of other vehicles in the platoon, enabling safe and reliable platoon formation. Using these platooning strategies, CACC-capable vehicles can increase the effective freeway capacity (van Arem, van Driel et al. 2006).

Shladover et al. (2012) conducted series of microsimulation experiments (informed by field-testing of CACC-equipped vehicles) to estimate the impacts of platooning CACC vehicles on freeway traffic flow, at multiple levels of market penetration. This research found that the marginal increase in capacity enhancement increases at higher market penetration levels. When the entire traffic flow stream was equipped with CACC capabilities, lane capacity was estimated to increase to 3,970 vehicles per hour, or nearly double current freeway lane capacities. Moreover, two evaluation alternatives were tested based on the rest of the non-CACC vehicle fleet: as conventional unconnected vehicles, and as CVs that can transmit "Here I am" (HIA) messages via DSRC-enabled V2V communication, to enable platoons to form behind them. Table 5.6 summarizes the estimated potential impacts of CACC, across various market penetration levels.

**Table 5.6: Estimated Impacts of CACC on Freeway Capacity (veh/hr/ln)**

| Method | Area Type | Facility Type | Benefit Type | Impact by market penetration | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | 0% | 20% | 40% | 60% | 80% | 100% |
| CACC | - | Freeway | Increase Capacity | 2100 | 2200 | 2350 | 2500 | 2900 | 3970 |
| CACC w/ HIA | - | Freeway | Increase Capacity | 2200 | 2350 | 2500 | 2900 | 3300 | 3970 |

While in theory the CACC-with-HIA implementation should work, in practice there may be reluctance on the part of road users. That is, the driver in a vehicle that can transmit an HIA message but is not CACC capable might likely object to CACC-capable vehicles platooning behind it with very short gap spaces. Instead, it is envisioned here that platoons of vehicles would be more likely to be self-organizing across CACC-capable vehicles only, with each vehicle in the platoon (including the lead vehicle) operating in self-driving mode, thus reducing potential anxiety, nervousness, or other discomfort by potential non-CACC lead vehicles. Therefore, for the subsequent analysis conducted in this report, figures from the CACC-only analysis method are used.

Furthermore, similar information may be obtained from other downstream V2V-capable vehicles that are not in a platoon (or from roadside infrastructure relaying this information). Using this information, CAVs can identify such downstream traffic flow conditions, and adjust their speeds accordingly (e.g., letting off the accelerator prematurely when a downstream vehicle brakes, to avoid harder braking later). This phenomenon results in overall smoother traffic flow, lower fuel consumption, and reduced delays, additionally benefiting following vehicles (connected or not) even at lower levels of market penetration. Atiyeh (2012) estimates that on congested freeways, such traffic flow smoothing algorithms could achieve speed increases of 8 to 13%.

Similarly, Englund et al. (2014) evaluated the potential impacts of cooperative speed harmonization (CSH) on a highly congested freeway interchange, which acted by strategically adjusting CAV speeds to integrate merging traffic flow streams. They found that CSH should decrease $CO_2$ emissions by 11% and travel time by 16%, and increase average speed up to 14%. Englund et al. (2014) conducted this research by simulating approaching vehicles that became grouped as they approached a convergence point at an on-ramp, thus resulting in fewer vehicles that would need to change lanes at the intersection. Milanés et al. (2011) conducted a similar evaluation using automated ramp metering and DSRC communication by enabling merging vehicles to fluidly enter major facilities, while avoiding congestion on the approach ramp. This was conducted in part by modifying the speed of the vehicles already on the main road, which in turn reduced the total effect of congestion on main facility. When using this strategy, total congestion delay experienced in the merge area was reduced between 7% and 16%.

At the surface street level, it should also be possible to achieve efficiency improvements, particularly at intersections. A CAV could communicate with a connected signal to improve operational efficiencies, enhancing existing signal detection system capabilities, and potentially accounting for modal consideration, as formulated in the Multi-Modal Intelligent Traffic Signal System algorithm (Head 2014). CAVs could coordinate acceleration and deceleration profiles in advance of a signal phase change, in order to minimize hard braking and acceleration. For example, strategically premature deceleration could allow a CAV to arrive just before the stop bar at the start of green, while rolling at 30 mph, thus effectively eliminating startup delay. Also, a small platoon of CAVs could simultaneously accelerate from stopped conditions, thereby removing startup time loss for every vehicle but the platoon leader.

Eventually, once all or almost all vehicles are equipped with CAV capabilities, tremendous intersection efficiencies may be possible, by facilitating alternative right-of-way assignment at signalized intersections (e.g., Autonomous Intersection Management, or AIM; Dresner and Stone 2008). The AIM protocol operates by assigning each vehicle approaching the intersection a dedicated time-space path, while ensuring that the path does not conflict with a previously assigned path of another vehicle. Yet in order to achieve such gains, it is necessary that very high market penetration levels are present, likely in excess of 90%. Therefore, potential signalized intersection benefits due to fundamental operational paradigm shifts like those proposed in AIM are not assumed in the analysis conducted in this report.

*Quantitative Estimates of Mobility Impacts*

In order to estimate the potential impacts of CAVs on congestion in Texas, the following assumptions and methodology were used. First, the relative levels of congestion were broken out between Austin, Dallas/Fort Worth, Houston, San Antonio, and other mid-sized Texas cities. Data from Schrank et al.'s (2015) Urban Mobility Report was then used to estimate base levels of congestion, segmented by peak vs. off-peak congestion, and freeway vs. surface street congestion, using prior values noted in Table 5.2. Next, equivalent peak hour freeway congestion was estimated using each of these cities' travel time indices, which relates average peak hour travel times to travel times in free flow conditions. The Bureau of Public Roads link performance function (Eq. 5.1) was then used to estimate average effective regional freeway traffic volumes, assuming link capacity of 2100 vehicles per hour per lane.

$$T_c = T_f \left(1 + \alpha \left[\frac{v}{c}\right]^{\beta}\right) \tag{5.1}$$

In Equation (5.1), $T_c$ represents congested link travel time, $T_f$ the link free-flow travel time, $v$ traffic volume, and $c$ link capacity, while α and β are volume/delay coefficients with parameter values of 0.83 and 5.5, consistent with Martin and McGuckin's (1998) findings.

Once current assumed traffic volumes were obtained, effective link capacity was increased by 50, 325, and 1335 vehicles per hour per lane at the 10%, 50%, and 90% market penetration levels, consistent with Shladover et al.'s (2012) earlier findings. Next, increasing traffic volumes were incorporated, due both to greater travel per CAV, and due to increased travel by other road users as they see their travel times fall. This resulted in total average VMT increases of 3%, 12%, and 26%, respectively, at the 10%, 50%, and 90% market penetration levels. After this calculation, a flat 10% reduction in delay was assumed across all scenarios, to account for the combined congestion impacts of freeway traffic flow smoothing, CSH, intelligent ramp metering, and other CAV applications. Resulting delay values were compared against initial delay, in order to estimate the total percentage of delay reduction across each of the market penetration scenarios.

Since off-peak delay freeway cannot be as readily computed as peak hour delay without more granular details (e.g., traffic volume assumptions, incidents that may have caused the delays, etc.) the same share of delay reduction was assumed as was computed for peak hour delays. For surface street arterials and collectors, delay reductions of 5%, 10%, and 15% were assumed at the respective 10%, 50%, and 90% market penetration levels. These were used to account for greater signal and vehicle operational efficiencies, with values consistent with the estimates used by Fagnant and Kockelman (2015). The resulting estimated potential congestion delay reductions across Texas may be seen in Table 5.7.

**Table 5.7: Estimated Impacts of CAVs on Freeway Traffic Congestion in Texas**

| City | Impact | Market penetration | | | |
|---|---|---|---|---|---|
| | | **0%** | **10%** | **50%** | **90%** |
| **Austin** | Annual Delay per Population (hr) | 24.4 | 23.0 | 20.8 | 14.7 |
| | Delay Reduction per Population (hr) | | 1.4 | 3.6 | 9.7 |
| | Congestion Cost Savings per Population | | $25 | $64 | $172 |
| | Regional Congestion Cost Savings ($M) | | $31 | $79 | $213 |
| **Dallas/Fort Worth** | Annual Delay per Population (hr) | 24.9 | 23.4 | 21.2 | 15.0 |
| | Delay Reduction per Population (hr) | | 1.5 | 3.7 | 9.9 |
| | Congestion Cost Savings per Population | | $26 | $65 | $175 |
| | Regional Congestion Cost Savings ($M) | | $246 | $621 | $1,670 |
| **Houston** | Annual Delay per Population (hr) | 29.4 | 27.7 | 25.0 | 17.7 |
| | Delay Reduction per Population (hr) | | 1.7 | 4.3 | 11.7 |
| | Congestion Cost Savings per Population | | $30 | $77 | $206 |
| | Regional Congestion Cost Savings ($M) | | $288 | $727 | $1,957 |
| **San Antonio** | Annual Delay per Population (hr) | 22.5 | 21.2 | 19.2 | 13.6 |
| | Delay Reduction per Population (hr) | | 1.3 | 3.3 | 8.9 |
| | Congestion Cost Savings per Population | | $23 | $59 | $158 |
| | Regional Congestion Cost Savings ($M) | | $86 | $216 | $581 |
| **Others**[16] | Annual Delay per Population (hr) | 15.0 | 14.2 | 13.2 | 11.3 |
| | Delay Reduction per Population (hr) | | 0.8 | 1.8 | 3.8 |
| | Congestion Cost Savings per Population | | $14 | $32 | $67 |
| | Regional Congestion Cost Savings ($M) | | $73 | $162 | $340 |
| **Statewide** | Congestion Costs ($M) | $13,079 | $12,319 | $11,185 | $8,078 |
| | Congestion Cost Savings ($M) | | $760 | $1,894 | $5,001 |
| | System-wide Congestion Reduction (%) | | 5.8% | 14.5% | 38.2% |

Meaningful congestion reduction may be achieved even at the 10% market penetration level, with an estimated total system-wide delay reduction of nearly 6%, accounting for $760 million in economic savings. By the 90% market penetration level, more than half of freeway congestion is assumed to be eliminated, with most of the remaining congestion due to collector and arterial surface street intersections. This results in a total system-wide delay reduction of more than 38%, for a cost savings exceeding $5 billion. Of course, readers should keep in mind that these figures are meant to represent order-of-magnitude estimates of potential outcomes, and that there remains a great deal of uncertainty surrounding how these CAV systems will ultimately be implemented.

### 5.1.5 Safety

*Potential Safety Impacts of Connected & Automated Vehicles*

Motor vehicle collisions have existed since the world's first engines were installed in horseless carriages: the first recorded gasoline-powered auto crash occurred in 1891, involving a vehicle that lost control and crashed into a hitching post (Soniak 2012). From that time, auto

[16] El Paso, Laredo, McAllen, Brownsville, Corpus Christi, and Beaumont.

manufacturers, civil engineers, planners, law enforcement, and others have sought to identify ways to reduce automotive crashes. In over 90% of incidents, the primary cause of the collision is human error, such as slow reaction time, poor sight, aggressive driving, drowsy driving, or other human factors (NHTSA 2008). While other environmental- and vehicle-related causes remain factors to be considered, this finding indicates a strong potential for reducing crash rates.

In this respect, Level 4 automation (when vehicles will be able to drive themselves for the entire trips without human intervention) may be the best option for reducing human errors. Here, the term *reducing* is used because human error will still exist, though it will be effectively transferred from the human driver to the human programmer coding the underlying logic and algorithms used to guide the vehicles' operations. This noted, the relative level of safety should improve as time and technology progress, since software and hardware developers can learn from and build upon past experiences. In contrast, each new 16-year-old driver must begin anew, so the difference in safe driving ability from one year's group of 16-year-olds to the next is likely negligible (or perhaps worse in some ways, given increasing smart phone distractions). This noted, it may take 20 years or more before vehicle automation technology can safely and reliably handle the same variety of environmental and roadway locations, conditions, and speeds that human drivers regularly drive on today.

As previously noted, this report seeks to examine the potential benefits from Level 3 to Level 4 automation, assuming CV technology. With safe driving responsibilities transferred from the human driver to the vehicle, it is useful to broadly understand the types of human errors that were primarily responsible for collisions, and how similar failures may be handled differently for CAVs versus human drivers. One way to frame these differences is in terms of perception (P), interpretation (I), judgment (J), and reaction (R, which in this case also represents action), or PIJR, a key variable used when considering stopping sight distance reaction times. Today, PIJR times required for CAVs are much shorter than PIJR times for human drivers, and it is possible that these times could be further reduced with advances in processing power. Using that underlying framework, this analysis broadly groups human failings into the following categories: intoxication (drugs or alcohol involvement), aggressive driving (characterized by speeding, erratic operation, or other prohibited maneuvers), inattention and distraction, judgement failure (failures to keep in lane or yield), and performance errors, with corresponding PIJR elements as follows:

- Intoxication (PIJR),
- Aggressive driving (JR),
- Distraction or inattention (P),
- Judgment failure (IJR), and
- Performance (PJR)

While it is unknown how many of these collisions may be completely avoided, educated estimates may be used to assess potential order-of-magnitude scales for potential crash reductions. Therefore, the following crash reduction factor (CRF) estimates are provided at the 10% market penetration level, using the following justification:

- *Intoxication (99%):* A vehicle cannot consume alcohol or ingest drugs. The closest analogy would be a malicious cyber-attack against one or more CAV, which should almost assuredly occur at a dramatically lower frequency than current rates of drunk or drugged driving in Texas. Therefore, a 99% CRF is assumed for crashes where intoxication was involved.

- *Aggressive driving (90%):* CAVs will likely be programmed to prohibit aggressive driving. This noted, it is still possible that a CAV could misinterpret conditions, or behave erratically due to sensor, software, or actuator failures, and thus behave similarly as an aggressive driver would. It is highly unlikely that these failures should be common, so a 90% CRF is assumed.
- *Inattention and Distraction (75%):* While it should be impossible for a CAV to become inattentive or distracted, it may encounter other errors due to sensor limitations or interpretation failures regarding information received from the sensors. Therefore, a 75% CRF is assumed, to account for these new errors that may be introduced.
- *Judgment failure (75%):* CAVs should be better at staying in their lanes than human drivers, since occasional willingness to drive outside of lane lines on curves, and other human behaviors will not apply. Similarly, range finders, communication abilities on CAVs, and other sensors may be used to better assess when a turn is safe to make (particularly compared to human drivers), and establish right of way for turning operations. However, since a CAV should still be able to misinterpret lane lines, pavement edges, safe turning decisions, and other judgements, a 75% CRF is assumed.
- *Performance Error (67%):* IIHS (IIHS 2015) notes that teenagers have crash rates at three times those of drivers over 20, while at a minimum, CAVs must be at least as safe as a good human driver. Therefore, a 67% CRF for causes due to inexperience is assumed to achieve this basic level of safety. Similar safety improvements are assumed for general performance-related crash causes, such as inadequate surveillance, overcompensation, panic/freezing, and poor directional control.
- *Other factors (50%):* Even after accounting for all aforementioned potential crash causes, it remains highly likely that CAVs will be required to be able to drive safer than a sober, attentive, experienced and relatively cautious human driver. Indeed, rider acceptance will likely demand this: a minor mistake resulting in a near-collision may be waived off with a human driver, though the same action would cause a dramatic loss of confidence in the self-driving capabilities of a CAV. In the event that a crash actually occurs, the loss of confidence may lead the owner to sell the vehicle outright. Therefore, a 50% CRF is assumed for all other crash types, at a range that is lower than other human failure CRFs, but still twice as safe as a human driver.

Additionally, it is assumed here that a crash where multiple of the above factors were involved that highest applicable CRF is applied. This may therefore underestimate the total possible crash reduction, since, for example, in a collision involving aggressive driving and distraction, both contributing factors would be addressed through CAV capabilities.

In subsequent years it is assumed that the level of safety will continue to improve for CAVs. Though it is impossible to truly appreciate how far they may drop, this report assumes that between the 10% and 50% market penetration level all collision rates are halved, and that collision rates are halved again between the 50% and 90% market penetration levels. Thus, for example, the 90% CRF for aggressive driving would become a 95% CRF at the 50% market penetration level and exhibit a 97.5% CRF at the 90% market penetration level. Therefore, total crash reduction potential is estimated for CAVs as shown in Table 5.8.

**Table 5.8: Assumed Crash Reduction Factors for CAVs**

| Crash Factor | Types of Human Error | CAV Market penetration | | |
|---|---|---|---|---|
| | | 10% | 50% | 90% |
| Intoxication | Alcohol, Drugs | 99% | 99.5% | 99.75% |
| Aggressive Driving | Speeding, driving too fast for curve or conditions, erratic operation, illegal maneuver, other prohibited driver errors | 90% | 95% | 97.5% |
| Distraction & Inattention | Internal and external distraction, inattention | 75% | 87.5% | 93.75% |
| Judgment Failure | Failure to keep in lane, failure to yield, misjudgment of gap or other's speed, false assumption of other's action | 75% | 87.5% | 93.75% |
| Performance | Inexperience / over-correction, inadequate surveillance, panic / freezing, sleep, heart attack | 66.67% | 83.34% | 91.67% |
| Other Factors | All other crashes | 50% | 75% | 87.5% |

NHTSA's (2015) Fatal Analysis Reporting System (FARS) database was then used across the set of 2013 Texas roadway fatalities to estimate the share of fatal collisions that were attributable to each of these factors. As noted previously, where more than one of these factors was observed for a single crash, the crash factor associated with the higher CRF was assumed (e.g., if alcohol and aggressive driving were both noted in a crash, the crash is attributed to intoxication and not aggressive driving, in order that crash reductions are not double-counted).

Similarly, NHTSA's General Estimates System (GES) database contains some of this information, though the collision data contained therein is more sparsely populated, making it difficult to truly get a sense of how crashes were attributed to each of these crash factors. Therefore, the set of critical reasons for the critical pre-crash events from NHTSA's (2008) Motor Vehicle Crash Causation survey is used here for non-fatal crashes, to estimate what total proportion of collisions is attributable to each of the various crash causes. This data is further augmented by non-fatal alcohol and drug-related crash information from the GES database, since drugs and alcohol are not listed as a critical pre-crash event, with resulting shares across the various crash factors shown in Table 5.9.

**Table 5.9: Shares of Fatal and Non-Fatal Crashes Attributable to Various Crash Factors**

| Crash Factor | Types of Human Error | % of Fatal Crashes | % of Non-Fatal Crashes |
|---|---|---|---|
| Intoxication | Alcohol, Drugs | 37.0% | 6.9% |
| Aggressive Driving | Speeding, driving too fast for curve or conditions, erratic operation, illegal maneuver, other prohibited driver errors | 23.1% | 17.5% |
| Distraction & Inattention | Internal and external distraction, inattention | 6.1% | 15.4% |
| Judgment Failure | Failure to keep in lane, failure to yield, misjudgment of gap or other's speed, false assumption of other's action | 8.3% | 6.7% |
| Performance | Inexperience / over-correction, inadequate surveillance, panic / freezing, sleep, heart attack | 2.0% | 35.8% |
| Other Factors | All other crashes | 23.5% | 16.2% |

*Quantitative Estimates of Safety Impacts*

In order to provide a quantitative estimate of the potential safety benefits of CAVs, it is necessary to understand the number, severity, and cost of crashes that Texas experiences on an annual basis, the shares attributable to various causes, and the potential for their future reduction through CAV capabilities. By applying these factors across three levels of market penetration (10%, 50%, and 90%), it is possible to estimate the total potential collision savings for CAVs as they enter the Texas transportation system. Table 5.10 summarizes the road safety implications and potential of CAVs for non-motorcycle crashes, Table 5.11 summarizes the same for motorcycle collisions (crash reductions here are assumed to be lower, since motorcycles are assumed to be non-automated and only enjoy safety enhancements gained through reduced crash exposure from other vehicles), and Table 5.12 summarizes implications across all road crashes.

**Table 5.10: Potential Crash Implications for CAVs, Non-Motorcycle Crashes**

| | CAV Market Penetration | | | |
|---|---|---|---|---|
| | **0%** | **10%** | **50%** | **90%** |
| # Crashes | 436,975 | 405,168 | 248,213 | 70,450 |
| # Injuries | 224,930 | 208,569 | 127,794 | 36,289 |
| # Fatalities | 2,905 | 2,669 | 1,588 | 412 |
| Economic Costs ($M) | $17,932 | $16,593 | $10,100 | $2,814 |
| Comprehensive Costs ($M) | $76,158 | $70,389 | $42,695 | $11,770 |
| Lives Saved | - | 236 | 1,317 | 2,493 |
| Economic Savings ($M) | | $1,339 | $7,832 | $15,118 |
| Comprehensive Savings ($M) | - | $5,769 | $33,463 | $64,388 |

**Table 5.11: Potential Crash Implications for CAVs, Motorcycle Crashes**

| | CAV Market Penetration | | | |
|---|---|---|---|---|
| | **0%** | **10%** | **50%** | **90%** |
| # Crashes | 8,854 | 8,693 | 7,898 | 6,998 |
| # Injuries | 7,669 | 7,530 | 6,841 | 6,061 |
| # Fatalities | 503 | 494 | 449 | 398 |
| Economic Costs ($M) | $1,172 | $1,151 | $1,046 | $926 |
| Comprehensive Costs ($M) | $7,056 | $6,927 | $6,294 | $5,576 |
| Lives Saved | | 9 | 54 | 105 |
| Economic Savings ($M) | | $21 | $127 | $246 |
| Comprehensive Savings ($M) | - | $128 | $762 | $1,479 |

**Table 5.12: Potential Crash Impacts for CAVs (Not Accounting for VMT Changes)**

| | CAV Market Penetration | | | |
|---|---|---|---|---|
| | **0%** | **10%** | **50%** | **90%** |
| # Crashes | 445,829 | 413,861 | 256,111 | 77,448 |
| # Injuries | 232,599 | 216,099 | 134,635 | 42,350 |
| # Fatalities | 3,408 | 3,162 | 2,036 | 810 |
| Economic Costs ($M) | $19,104 | $17,744 | $11,146 | $3,741 |
| Comprehensive Costs ($M) | $83,214 | $77,316 | $48,989 | $17,347 |
| Lives Saved | | 246 | 1,372 | 2,598 |
| Economic Savings ($M) | - | $1,361 | $7,958 | $15,364 |
| Comprehensive Savings ($M) | - | $5,898 | $34,225 | $65,867 |

To these estimates, an added *exposure factor* must be applied, to account for the higher levels of VMT and resulting increased collision risk that will be experienced. As previously mentioned, different VMT changes are expected in rural vs. urban areas, and with differing market penetration levels. While urban areas were projected to experience VMT increases of 3%, 12%, and 26% for 10%, 50%, and 90% of market penetration, respectively, in rural areas these same values were estimated at just 1%, 5%, and 9%. This analysis then assumed that increasing VMT as a measure of exposure is directly proportional to the expected number of collisions. The final collision estimates were then achieved by applying these VMT growth factors to the earlier urban/rural crash split shares, and merging them with the potential CAV impacts estimated in Table 5.12. From this, Table 5.13 was generated, which summarizes the total estimated potential impact of CAVs on safety in the state of Texas.

**Table 5.13: Potential Statewide Crash Implications for CAVs**

| | CAV Market Penetration | | | |
|---|---|---|---|---|
| | **0%** | **10%** | **50%** | **90%** |
| # Crashes | 445,829 | 419,901 | 266,082 | 83,475 |
| # Injuries | 232,599 | 222,080 | 148,993 | 48,401 |
| # Fatalities | 3,408 | 3,224 | 2,211 | 955 |
| Economic Costs ($M) | $19,104 | $18,020 | $11,932 | $4,292 |
| Comprehensive Costs ($M) | $83,214 | $78,575 | $52,590 | $20,024 |
| Lives Saved | - | 184 | 1,197 | 2,453 |
| Economic Savings ($M) | - | $1,085 | $7,172 | $14,813 |
| Comprehensive Savings ($M) | - | $4,639 | $30,624 | $63,190 |
| % Reduced Comprehensive Crash Costs | - | 5.6% | 36.8% | 75.9% |

Taken together, these results indicate that CAVs could potentially save around 185 lives per year on Texas roads, even at the 10% market penetration level. With 90% market penetration, annual motor vehicle crash fatalities could be cut to almost a quarter of their current levels, leading to comprehensive collision cost savings in excess of $62 billion. Importantly, motorcyclists are expected to comprise nearly half of the remainder of fatal crashes at this market penetration level, with much of the remainder caused by non-CAVs. CAVs will still likely be responsible for collisions, (or even some fatalities, as projected here), though the key takeaway is the magnitude of the tremendous safety potential that CAVs might bring. As with the estimated congestion impacts, readers should remember that these estimate represent order-of-magnitude projections of potential outcomes, and there remains a great deal of uncertainty surrounding the ultimate improvements in safety that will eventually come to pass.

### 5.1.6 Productivity and Leisure

As drivers are freed from the task of operating their vehicles, they will gain the ability to focus their attention and efforts elsewhere, through relaxing, working, surfing the internet, or engaging in other activities that were previously not possible to do while driving (at least safely). This should therefore result in added benefits stemming from CAVs, in terms of productivity gains and added leisure time for former drivers.

Here, it is assumed that productivity and leisure gains will be realized by the former driver of each CAV based on the time spent previously driving, but now available for other tasks. On average, 335 hours are spent driving per year per Texan, estimated based on Urban Mobility Scorecard data (TTI 2014). From this dataset we obtained each city's daily travel distance (VMT) by freeway and arterial, as well as Travel Time Index, percentage of congested travel (% of VMT), and number of auto commuter. Additionally, we assumed that free flow speed of freeway and Arterial as 70 mph and 30 mph respectively. Using equation (5.2), we can estimate the yearly travel time per Texan:

$$T_i = \sum_i \sum_j \left( \frac{\left(\frac{FFS_j}{VMT_{ij}}\right) \times TTI_i \times PC_j + \left(\frac{FFS_j}{VMT_{ij}}\right) \times PU_j}{C_i} \right) \times 365 \tag{5.2}$$

Where:

$T = Yearly\ Driving\ time$
$FFS = Free\ Flow\ Speed$
$VMT = Daily\ Travel\ Distance$
$TTI = Travel\ Time\ Index$
$PC = Percentage\ of\ Congested\ Trip$
$PU = Percentage\ of\ Uncongested\ Trip$
$C = Number\ of\ Auto\ Commuter$
$i = City$
$j = Freeway\ or\ Arterial$

Using USDOT guidance regarding personal travel (Endorf, R. 2015), existing values of travel time were assumed to be equal to half the median wage rate ($16.18 for Texas, BLS 2014), and gains from productivity and leisure were estimated to be 50% of current travel time valuations, consistent with MacKenzie et al. (2014) and Gucwa (2014). This means that each CAV should deliver approximately $1,357 per year in monetized time benefits to their users.

### 5.1.7 Summary Analysis

Analysis results from prior sections of this report may be drawn from in order to summarize the potential impacts of CAVs on the transportation system, across mobility, safety and productivity/leisure dimensions. This may be used in combination with anticipated future costs of vehicle automation, in order to more fully understand the potential impacts of CAVs in Texas.

Here, added purchase price costs for automation and connectivity capabilities (on top of base vehicle costs) are assumed to be $10,000 at the 10% market penetration level, $5,000 with 50% market penetration and just $3,000 in added cost once CAV market penetration levels reach 90%. These values are consistent with estimates from Southwest Research Institute's Steve Dellenback (2012) and Volvo's Erik Coelingh (ETQ 2012). A 10% discount rate is also assumed, which is higher than the 7% rate required for federal TIGER grant applications, to account for the greater uncertainty surrounding CAVs. These cost and discount rate values are consistent with those used in prior research conducted by Fagnant and Kockelman (2015).

The benefits from CAV were calculated on a per vehicle basis for comparing the cost of automation and connectivity capabilities. In this research, we assumed a baseline of Texas' existing 23.88 million vehicles to estimate these figures, though the true number of vehicles may likely increase along with Texas' population in future years (TxDOT 2014). An 11.4 year average CAV life span was also assumed for calculating net present value, based on current data for conventional vehicles (USDOT 2014). This noted, it is also possible that a substantial number of CAVs may have shorter lifespans, specifically for SAVs which would be used more intensely during any given year.

Table 5.14 summarizes the various safety and mobility benefits that may be gained across Texas' transportation system, while comparing them to anticipated added CAV costs, from an order-of-magnitude perspective:

**Table 5.14: Summary of Anticipated CAV Impacts across Texas**

| | | CAV Market Penetration | | |
|---|---|---|---|---|
| | | **10%** | **50%** | **90%** |
| Benefits | Congestion reduction ($/Veh/Year) | $318 | $159 | $233 |
| | Economic crash savings ($/Veh/Year) | $454 | $601 | $689 |
| | Comprehensive crash savings ($/Veh/Year) | $1,943 | $2,565 | $2,941 |
| | Productivity and leisure ($/Veh/Year) | $1,357 | $1,357 | $1,357 |
| | Sum of benefits ($/Veh/Year) | $3,618 | $4,081 | $4,530 |
| Costs | Price of automation and connectivity capabilities ($/Veh) | $10,000 | $5,000 | $3,000 |
| ***Net Present Values*** (using comprehensive crash cost savings) ($/Veh) | | $13,960 | $22,024 | $27,000 |
| ***Benefit-Cost Ratios*** (using comprehensive crash cost savings) | | 2.4 | 5.4 | 10.0 |

These results indicate that the introduction of CAVs may have significant potential for delivering significant benefits to the traveling public. Even at just 10% of market penetration, $13,960 in net benefits would be realized over the 11.4-year life of the CAV, after the $10,000 cost of automation and connectivity is removed. At all levels of market penetration, comprehensive crash cost savings represent the largest share of benefits, though if only economic costs are assumed, productivity and leisure benefits become most important. With 90% of market penetration, total lifecycle benefits rise to over 10 times the initial added costs of automation and connectivity. Also of note, not all of these benefits would be realized directly by the CAV owner or user. Some of the crash benefits would accrue to other road users (through reduced risk), and the benefits from congestion reduction effects would be experienced by all motorists.

## 5.2 Updated Benefit-Cost Analysis

### 5.2.1 Assumptions

*Mobility & Congestion Impacts*

- Due to the expected increases in vehicle-miles-traveled (VMT) due to eventual Level 4 automation, the method of TM 3 of 6847 assumed a 20% increase in vehicle-miles traveled (VMT) at the 10% CAV market penetration (MP) level. Likewise, a 15% increase and 10% increase in VMT per CAV are assumed at the 50% and 90% MP levels, respectively.
- Since CAVs are eventually expected to travel with smaller headways, effectively increasing capacity, latent demand from this effective capacity increase is also anticipated. Demand elasticities of 0.4, 0.2, and 0.1 are assumed at the 10%, 50%, and 90% CAV MP levels. These assumptions stem from the 0.74 average demand elasticity

with respect to highway miles found by Cervero (2001)'s review of literature. It is not expected that demand elasticities with respect to CAV miles driven will be as high.

- There is much debate about to the extent to which shared autonomous vehicles (SAVs) will achieve popularity in the future. SAVs will be Level 4 AVs that are owned by transportation network companies. (TNC) or some other entity. It is assumed that half of all CAV trips will be served by SAVs at the 10%, 50%, and 90% CAV MP levels.
- Expected increases in capacity derive from CAVs' use of cooperative adaptive cruise control (CACC), which enables each CAV to communicate with other vehicles on the roadway via dedicated short-range communication (DSRC) so that groups of vehicles form with smaller headways than currently observed with human-driven vehicles. Additionally, the method assumed that conventional vehicles were not equipped with a "Here I am" module, which allows CAVs to communicate with and utilize conventional vehicles in the formation of platoons. Thus, benefits were only derived from CAVs using CACC with other CAVs. A base link capacity of 2100 vehicles/hour/lane was assumed for the base case (0% CAV). Effective lane capacity was assumed to increase to 2,150, 2,425, and 3,435 vehicles per lane at the 10%, 50%, and 90% MP levels, respectively. Assumptions made on the increases in lane capacity at the three market penetration levels due to CACC were consistent with the findings of Shladover et al. (2012).
- A flat 10% reduction in delay on freeways was assumed for all three market penetration scenarios during peak and off-peak. This assumption accounted for the combined congestion impacts of freeway traffic flow smoothing, cooperative speed harmonization (CSH), intelligent ramp metering, and other CAV applications.
- For surface streets, arterials, and collectors, delay reduction of 5%, 10%, and 15% were assumed at the respective 10%, 50%, and 90% MP levels. These estimates were consistent with those made by Fagnant and Kockelman (2015).

*Safety Effects*

- The crash reduction factors that were assumed for each of the five crash reduction factors are shown in Table 5.15. Based on the crash reduction factors (CRFs) assumed at the 10% CAV MP level, the collision rates are assumed to be 50% less at the 50% MP level, and 75% less at the 90% MP level.

**Table 5.15: Assumed Crash Reduction Factors for CAVs**

| Crash Factor | Types of Human Error | CAV Market Penetration | | |
|---|---|---|---|---|
| | | 10% | 50% | 90% |
| Intoxication | Alcohol, drugs | 99% | 99.5% | 99.75% |
| Aggressive Driving | Speeding, driving too fast for curve or conditions, erratic operation, illegal maneuver, other prohibited driver errors | 90% | 95% | 97.5% |
| Distraction & Inattention | Internal and external distraction, inattention | 75% | 87.5% | 93.8% |
| Judgment Failure | Failure to keep in lane, failure to yield, misjudgment of gap or other's speed, false assumption of other's action | 75% | 87.5% | 93.8% |
| Performance | Inexperience / over-correction, inadequate surveillance, panic / freezing, sleep, heart attack | 66.7% | 83.3% | 91.7% |
| Other Factors | All other crashes | 50% | 75% | 87.5% |

- Of the five factors, if a crash in the FARS database was attributed to more than one of the five factors, the crash factor with the higher CRF was assumed for that crash. This assumption ensured that crashes were not double-counted.
- To account for the expected increase in demand resulting from CAV use, the higher levels of VMT were assumed to increase the expected amount of collisions in a proportional manner from the original collision estimates. The researchers assumed VMT increases of 3%, 12%, and 26% for the three respective MP levels in urban areas. Meanwhile 1%, 5%, and 9% VMT increases were assumed in rural areas at the 10%, 50%, and 90% MP levels.

*Productivity and Leisure*

- The value of travel time was assumed to be half of the 2014 median wage rate in Texas, which was $16.18 per hour according to the U.S. Bureau of Labor Statistics (BLS, 2014)
- Benefits from productivity and leisure were assumed to be 50% of the travel time valuations of Texas drivers.

*Costs of Automation and Connectivity*

- Purchase price costs for adding automation and connectivity capabilities were assumed to be $10,000, $5,000, and $3,000 at the 10%, 50%, and 90% MP levels.
- Texas' existing 23.88 million vehicles was assumed for calculating CAV benefits and costs per vehicle.
- An 11.4-year project life and 10% discount rate were assumed. The relatively high discount rate was used to account for the uncertainty in estimating benefits and costs for

CAVs. The project life assumption is based on the average life span of a conventional vehicles.

*Updates to Assumptions*

To further improve the method used to estimate benefits and cost implications of CAV use in Texas, parameter assumptions were updated with the results of autonomous vehicle research by UT-Austin. The updates are organized by the sub-sections listed earlier in Section 2.

*Mobility & Congestion*

A flat 10% reduction in delay benefits from CAV use on freeways was assumed in the original methodology. Because of the many factors that impact the amount of delay experienced on roadways, this assumption was made on simplistic grounds due to the lack of data and certainty on how CAVs will impact freeway use. Nonetheless, it is expected that CAV use will reap significant mobility benefits, but the magnitude of the benefits at each respective market penetration level is also uncertain. In TM 5 of project 0-6847, mixed traffic containing both HVs and CAVs was simulated on several freeway networks in Austin[1]. The links in the networks were simulated using the cell transmission model (CTM). The researchers assessed the impact of CAVs on two city networks in Austin. When only using traditional signals in their networks instead of new alternative methods of intersection management, there was a 26%, 36%, 45%, and 51% reduction in total travel time at the 25%, 50%, 75%, and 100% market penetration (MP) levels. When integrating CAVs into the simulations, the researchers assumed headways of only 0.5 sec for CAVs, which may not be feasible at the lower CAV MP levels due to concerns about liability. Because of various factors that have not been accounted for in simulations yet, the 10% reduction in delay assumption was made to be conservative. Early simulations as performed in this project show that some variation in delay reduction should be experienced as CAV market penetration rises. Additionally, since familiarity with CAVs should grow as more CAVs are adopted on the market, it is reasonable to assume that Texans' comfortableness with smaller headways should increase as well. Thus, it is recommended that the flat reduction in delay on freeways be changed to **10%, 15%, and 20%** at the 10%, 50%, and 90% CAV MP levels. The simulations from TM 5 from 6849 show much larger reductions in travel times using only signals, which show that the new assumptions maintain conservatism. It is expected that fully realized and optimized autonomous intersection management should reap further reductions in delay.

*Productivity and Leisure*

In Section 2, a random survey of Texans was conducted. This survey asked the respondents what their willingness to pay (WTP) to save 15 minutes of travel time. After excluding the respondents who answered $0 WTP, the average WTP of 1,364 Texans was $9.50. Scaling this value to an hourly basis, the average VOTT was $27.20/hour. The original methodology used a VOTT of $16.18/hour, which was half of the 2014 median wage rate for Texas; according to the U.S. Bureau of Labor Statistics. Since the figure obtained in TM 4 of 6849 was produced from a random sample of Texans, it is more representative of the opinions of Texans on saving travel time than a proportion of the median wage rate. It is recommended that the ***VOTT used in estimating congestion benefits*** from CAV use be ***increased from $16.18/hour to $27.20/hour***. It is anticipated that changing the VOTT parameter will increase the estimated benefits from delay reduction.

## 5.3 Locations in Texas for CAV Testing

This section identifies roadways and intersections in Texas that could serve as testbeds for assessing the effectiveness of strategies related to CAV use. Locations must be carefully selected so that initial tests relating to CAVs are given the highest chance of showing successful results. In other words, the anticipated benefits of CAV use may not be realized if initial testbeds do not show positive results, which could motivate state agencies and other interest groups to become less interested in CAV development. Potential testbeds are identified as highway segments or intersections that can be used testing CAV technologies. The roads and intersections that are proposed for testing purposes are only recommendations and should be used mainly to further the discussion of testing CAV technologies. Roads or intersections are classified into three levels of testing: preliminary, intermediate, and advanced. The details of testing procedures are not discussed here as that isn’t the focus of this task. These stages are designated to indicate roads that could be used to test CAV platooning.

### 5.3.1 CAV Light-Duty Vehicle Platooning

Reduced headways from CAV use will increase the capacity of roadways. However, it is important that testing of light-duty platooning be performed to help further the development of platooning technology. Potential test corridors include highways in Texas that experience significant congestion. TxDOT maintains on a list of the 100 most congested corridors in Texas. For preliminary testing of CAV platooning, it is more feasible to begin testing on corridors that will most likely prove easier on which to test CAV technologies rather than opting for the top congested roads in Texas where the largest benefits may be realized. A relatively smaller testing scale will increase the probability of obtaining successful results. The list for year 2015 is compiled by the Texas A&M Transportation Institute, which uses 2014 traffic speed data for estimating delay. In addition to the top 100 congested roads published by TxDOT, the list by TTI includes over 1600 more TxDOT road segments that are ranked by congestion level. The level of congestion ranges from around 975,000 person-hours of delay per year to just one person-hour of annual delay on the roads contained in the TTI list.

It is expected that CAV use will first occur primarily in urban areas instead of rural areas. When selecting corridors for testing light-vehicle platooning, picking a group of roads that have geographic diversity within the state will help minimize any biasing of results to patterns of one urban area. The suggested roads were limited to the six largest counties in Texas by population: Harris, Bexar, Dallas, Travis, Tarrant, and El Paso. The criteria presented in Table 5.16 was developed for determining possible roadway segments for CAV light-vehicle platooning testing.

**Table 5.16: Criteria for Selecting Potential Roadway Segments for Light-Duty Platooning Testing**

| Testing Level | Length (miles) | Annual Delay per mile (person-hours) |
|---|---|---|
| Preliminary | > 5 | 30,000 to 60,000 |
| Intermediate | > 5 | 60,000 to 100,000 |
| Advanced | > 5 | >100,000 |

Roads shorter than five miles were not considered to ensure enough length was provided to fully observe platooning effects. The roads that were selected for the preliminary, intermediate, and advanced testing levels are shown in Tables A-1, A-2, and A-3 respectively in Appendix A. Though the highest benefits will be realized from implementing CAV technologies on the roadways with higher levels of congestions, the roadways suggested for preliminary testing are expected to have a relatively higher chance of success with early and less familiar testing procedures than the roadways selected for intermediate or advanced testing, which will require more rigorous testing procedures to meet the scale. This qualitative approach is implied throughout the rest of the section.

### 5.3.2 CAV Truck Platooning

As Texas has the second largest population of any U.S. state, trucks carry a considerable amount of goods throughout the state. Though platooning for light-vehicles and trucks will produce a similar type of benefit, it will be important to select roads for testing truck platooning that experience notable truck delay. When observing TTI's 2015 list of most congested roads, many roads have a significant amount of both light-duty and heavy-duty delay. But some roads contain little or no truck delay. Annual truck delay per mile ranges from a peak of just under 115,000 annual person-hours to less than two person-hours annually. A similar approach is taken for suggesting roads that can serve as testbeds for CAV truck platooning. The following criteria (Table 5.17) are used for identifying potential roadway segments from TTI's list of the most congested roadways in Texas. Since many trucks carry freight over long distances, the selected roads were not limited to the six largest counties as with light-duty platooning. The suggested roads for preliminary, intermediate, and advanced testing are listed in Appendix A (Tables A-4, A-5, and A-6).

**Table 5.17: Criteria for Selecting Potential Roadway Segments for Truck Platooning Testing**

| Testing Level | Length (miles) | Annual Delay per mile (person-hours) |
|---|---|---|
| Preliminary | > 5 | 10,000 to 20,000 |
| Intermediate | > 5 | 20,000 to 50,000 |
| Advanced | > 5 | >50,000 |

### 5.3.3 Texas Intersections as Potential Test Beds

Reducing the number of intersection-related crashes is a significant potential benefit of CAVs. New technologies are being developed, such as Cooperative Intersection Collision Avoidance Systems (CICAS), should be able to reduce crash frequencies at intersections.

According to 2008 crash data from databases maintained by NHTSA, around 40% of the 5.8 million crashes reported that year were intersection-related (NHTSA, 2010). Indirectly related to safety, researchers have been working on developing alternative methods of intersection management that can improve throughput. This new form of intersection management, known as autonomous intersection management (AIM), is intended to allow CAVs to reserve space at an intersection, which is similar in form to a slot-system. CAVs are allocated space by the automated intersection manager, which allocates space on a first-come-first-serve basis. Researchers have been working on various algorithms and simulations to test the potential of this alternative form of intersection management (Dresner & Stone, 2008; Levin & Boyles, 2015; Au et al., 2016). Improved efficiency at intersections using fully optimized AIM systems is expected to coincide with a reduction in intersection-related crashes.

When exploring intersections that serve as potential testbeds for testing new intersection technologies, it is infeasible to examine every intersection in the state and determine their average control delays. A more feasible approach is identifying general locations in Texas where intersections could most likely be used as testbeds. Since CAV use is expected to begin in urban areas, and then expand to rural areas at higher market penetration levels, the intersection testbeds should be in or near the larger cities in Texas. Figure 5.3 maps the TxDOT districts discussed.

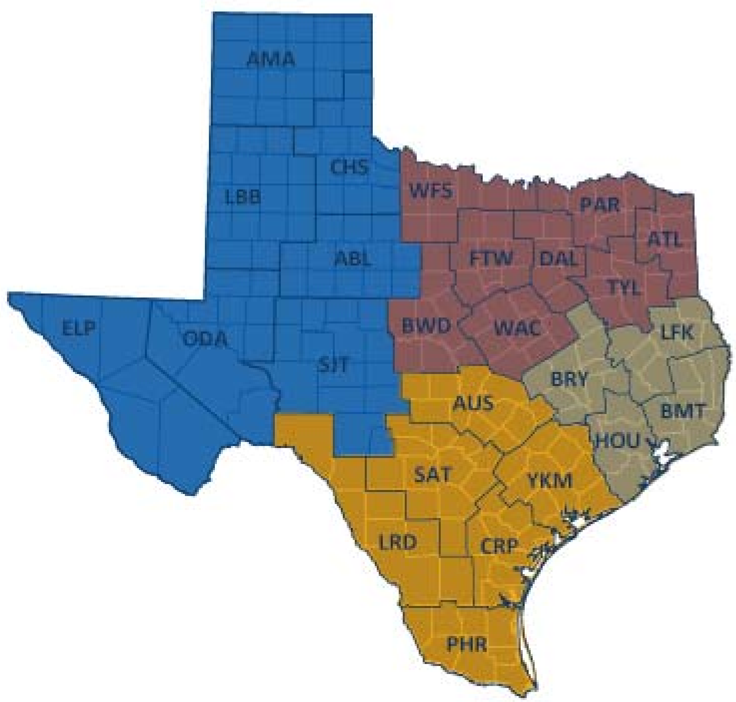



*Figure 5.3: TxDOT District Map*

Intersections that are selected for testing should be close to urban areas to best simulate traffic conditions in those highly populated areas. In order to do this, intersections testbeds should be located in the six most populated TxDOT districts: Houston (HOU), Dallas (DAL), San Antonio (SAT), Austin (AUS), Fort Worth (FTW), and El Paso (ELP). A general recommendation would be to begin initial testing on intersections in counties within these six districts that are not the respective district's most populated county. For example, if potential intersections are being looked at in the Austin District, it is reasonable to assume that lower risk and difficulty in testing would be experienced if an intersection in Williamson or Hays Counties is selected. More granular details should be incorporated into the decision process, such as intersection skew, control delay, adjacent land use, and proximity to other signals. The last factor should be taken into account when conducting tests that involve coordination between signals.

# Chapter 6. Conclusions

The general public is the primary beneficiary of smart driving technologies. AVs have the potential to fundamentally transform the act of driving, by offering an array of safety and driver-assistance features. First and foremost, automated vehicles can substantially reduce or mitigate crashes. Second, smart driving technologies will free the drivers from driving tasks, and thus reduce stress, especially in congested conditions. Third, they can provide critical mobility to the elderly and disabled. Fourth, they have the potential of increasing road capacity, saving fuel, and lowering emissions, if automatic steering algorithms are carefully developed. Complementary trends in shared rides and vehicles may lead us from vehicles as an owned product to an on-demand service, and mitigate the need for parking space and change land use patterns, including changes to current zoning codes that often require specific parking requirements per occupant or dwelling type. Additionally, the passenger compartment may be transformed: former drivers may be working on their laptops, eating meals, reading books, watching movies, and/or calling friends—safely. Though there are many benefits to this new technology once implemented, a number of barriers are anticipated to challenge the development and implementation of intelligent driving technologies, especially advanced autonomous technologies (Level 3 and Level 4). Some of these major barriers include the high cost of these new vehicles, security and privacy issues on a large-scale network that can be prone to cyber-attacks, and smoothly transitioning this technology in a large-scale adoption. Other barriers facing the intelligent driving technologies include legislation (liability and licensing), insurance, and social equity. These CAVs, SAVs, and CVs will also require more information from the roadways as well as supporting infrastructural components to function properly (such as lane markings and signs).

The survey results offer insights about Texans' current adoption of, WTP for, and interest in CAV technologies, while helping traffic engineers, planners and policymakers forecast long-term (year 2015-2045) adoption of these technologies under three different technology-acquisition-cost scenarios (i.e., 1%, 5%, and 10% annual price-reduction rates). Among Level 1 technologies, traffic sign recognition is the least interesting (52.5% of respondents reported $0 WTP), currently the least adopted (2%), and anticipated to have the lowest level of future adoption (in 2045) by Texans. Blind-spot monitoring and Emergency automated braking are the two most interesting technologies for Texans, with the highest adoption rate (59.4%) among Level 1 technologies in 2045 at a 10% price reduction rate. ESC has the highest current adoption rate (21.7%), and is anticipated to have the highest (59.9%) and second-highest (56.9%) future adoption rates (among Level 1 Technologies) at the 5% and 10% price reduction scenarios. More than half of respondents are not willing to pay anything to add advanced automation technologies (Level 3 and Level 4) to their current vehicles. Average WTP (of the respondents with a non-zero WTP) to add connectivity and Level 3 and Level 4 automations are $110, $5,551, and $14,589, respectively. The future adoption rate of connectivity is comparable with the second-most adopted Level 1 technology in the future. Respondents also felt more comfortable knowing that their vehicles themselves would be connected through open communication, however felt the most uncomfortable when knowing that they, as owners, are liable for any accidents that occur with the vehicle. Interestingly, roughly the same shares of respondents reported WTP of $0 to use AVs for short-distance (39.2%) or long-distance (37.3%) trips. The average number of long-distance trips (over 50 miles) is reported to increase by 1.3 (per person per month) due to the adoption of AVs. Because this is the current perceptions of Texans, as they learn more about CAV technologies and experience more of the technology first hand, their responses may change. More survey work is required elsewhere in the U.S. as well as in other countries, all over time.

In order to see cost improvements with CAVs, values are assigned to different metrics of transportation. VMT is predicted to rise, as travelers experience falling values of travel time (easier travel), CAVs travel unoccupied/empty, and inter-vehicle coordination and incident reductions effectively improve network capacity. Even with rising VMT, congestion may fall overall due to platooning, speed harmonization, cooperation with "smart" infrastructure, and fewer crashes. CAVs will no longer be prone to human errors, such as intoxication and distraction, resulting in fewer collisions and fewer fatality crashes. Moreover, as SAVs become a viable new transport mode, household vehicle ownership should fall, particularly in urban areas. Summary results indicate that comprehensive crash savings represents the largest potential gain (over $2,000 per privately held CAV per year), though benefits from added productivity and leisure time also comprises a substantial portion of the total benefits (at roughly $1,300 per driver that shifts to automated travel per year). Congestion benefits are also apparent, though much smaller in magnitude (since total travel delays are much lower in value to begin with). However, if targeted measures are used (e.g., smart intersections with very high CAV adoption rates), and innovative demand management strategies are undertaken (e.g., increased ridesharing using SAVs), it may be possible for each CAV to offer greater congestion benefits. In all, this work indicates that the lifecycle value of each privately held CAV is likely to result in over $15,500 in net benefits at the 10% market penetration level (after reflecting added automation costs), rising to over $30,000 per vehicle by the time 90% market penetration rates are reached. With CAVs we foresee an undoubted improvement in safety of all vehicles on the road as market penetration increases as CAVs are safer vehicles.

This report also describes several different models used to closely simulate AV behavior. Although AVs hold much potential, visually conveying the benefits to the public is an essential task and complex traffic models are required to simulate the predicted AV behaviors. First, a four-step planning model was used including trip generation, trip distribution, modal split and choice, and traffic assignment for AV and HV flow distribution. This static four-step model, simulates the effect of AVs on demand and route choice by including AV round trips which involves AVs dropping off passengers at locations and then leaving to avoid parking costs. This cut in parking cost can affect trip/route choice and further increase demand as it becomes more cost-effective to use an SAV or CAV to commute. Repositioning trips may increase SAV travel times, however far less SAVs are required to support a large population of travelers, however, with dynamic ride sharing involved, SAVs can cut times and use less vehicles on the road to do so, picking up three or four passengers at a time and taking them to similar destinations. This model will be able to show the effects of AVs on demand and route choice and their new generalized cost's effect on trip, mode, and route choice as well. Next, a multi-class extension of the CTM was introduced. AVs have the potential to improve link and intersection traffic behavior, since lower computer reaction times may admit reduced following headways as well as increase capacity and backwards wave speed.

To provide a framework for analyzing effects of these AVs on city networks, the multi-class CTM is used in conjunction with a shared road DTA model for HVs and AVs. The multi-class CTM is presented for vehicles traveling at the same speed with capacity and backwards wave speed a function of class proportions. A collision-avoidance car-following model incorporating vehicle reaction time is used to predict how reduced reaction times might increase capacity and backwards wave speed. These models are generalized to an arbitrary number of classes to allow for different AVs certified for different reaction times. These models also use continuous flow so that SBDTA models built on continuous flows may incorporate these multi-class predictions. With the second part of a shared road DTA model is the intersection control which involves secondary and unconventional alternatives to the traditional traffic signal such as a FCFS TBR system for 100% AVs that could potentially increase efficiency by decreasing travel times as well. TBR intersection control for AVs has the potential to reduce intersection delays beyond optimized traffic signals.

Because modeling such a finely aggregated intersection in TBR is so robust and computationally demanding, a conflict region model was developed to offer a much more tractable model and more practical simulation in terms of run time. Previous work studied prioritizing requests via FCFS or holding auctions at intersections, but the possibilities are infinite. Furthermore, although selfish routing behavior could affect the benefits of the reservation prioritization, reservation control has not been studied with user equilibrium routing due to its microsimulation definition. Future work will include developing traffic models that include vehicle automation of several levels and running these models using the adapted simulator. Preliminary results show that adaptive micro-tolling can achieve up to a 30% decrease in the average travel time within a road network. Finally, in regards to the methodology of models and simulations, this report presented an event-based framework for implementing SAV behavior in existing traffic simulation models. We demonstrated this framework by implementing SAV behavior in a CTM-based DTA simulator. The framework relies on two events independent of traffic flow models: travelers calling SAVs, and SAVs arriving at centroids. This allows comparisons with personal vehicle scenarios through solving traffic assignment in the same simulator.

Using the defined above, road-sharing DTA simulations were run using a multi-class CTM and a conflict region model (for intersection control) for AVs, HVs, and different proportions of the two together with traditional traffic signals. Our team also varied demands for each network tested, to observe trends as demands were increased to 100% for the network tested. Finally, simulations with 100% AVs were run on each network with FCFS TBR systems at intersections and merge/diverge ramps on highways. The networks tested included 2 arterial networks, 3 freeway networks, and 1 downtown network, which were all part of the Texas 100 top most congested locations and intersections, with the purpose of being able to apply our results to most other network scenarios. It was observed that increasing the proportion of AVs always decreased travel times in all networks tested due to the reduced reaction times of AVs causing closer following headways and increased capacities, with larger benefits in freeway networks, naturally. The TBR system, however, did not always do better than traditional signals in terms of travel time. For arterial regions, reservations were beneficial in some situations but not in others. On Congress Avenue, a long arterial without progression, reservations improved travel times. However, at the Lamar & 38th Street intersection, reservations gave greater priority to vehicles entering from local roads. Since intersections were so close together, this created queue spillback and greater congestion from using reservation controls. This was due to the FCFS policy: vehicles were prioritized according to how long they had been waiting. In contrast, signals allowed more freedom in capacity allocation, and were optimized to give arterials a greater share of the capacity. On freeway networks, the effects of reservations were again mixed. On US-290, which uses signals to control access, reservations were an overall improvement. In other freeway networks, reservations were worse than merges/diverges. In the downtown Austin grid network, reservations resulted in great reductions in travel times. The downtown Austin network saw a near 78% reduction in travel times across the network as congested intersections did not pose as great a problem as in the Lamar & 38th scenario, because the larger downtown network allowed for more dynamic route choice and avoidance of such a problem.

Moreover, the simulations do not consider corridor or intersection use by pedestrians and cyclists, which will reduce capacities and increase travel times. If signals are foregone, special accommodations will be needed for pedestrians and cyclists.

Finally, this report also described a model to analyze the impact of CAV availability on AM peak transit demand. CAVs allow the option of a drop-off and return trip to avoid parking costs, incurring only additional fuel consumption, so a generalized cost function of travel time, monetary fees, and fuel was created to model the cost of a trip. On the other hand, CAV use increases road capacity, reducing travel times. The model was tested on the Austin downtown network, including bus routes. Results indicated that parking cost was a main incentive for transit, and that avoidance of parking costs through CAV round-trips resulted in both an increase in CAV round-trips relative to one-way and park trips and a decrease in transit demand. However, only modest increases in average link speed were observed. These results are likely due to two factors: first, CAVs have a reduced following headway resulting in higher capacity, which is included in the travel time function; second, most repositioning trips are away from downtown, whereas most traveler trips are moving towards downtown, so they use somewhat different links.

# References


Andrew, M., Richard, B., Vikki, F., Justin, M., Tammy, E. T., & Blanco, M. (2013). Human Factors Evaluation of Level 2 and Level 3 Automated Driving Concepts: Concepts of Operations. NHTSA.

Au, T., Zhang, S., & Stone, P. (2016). Autonomous Intersection Management for Semi-Autonomous Vehicles. New York: Routledge. Retrieved from http://www.cs.utexas.edu/~pstone/Papers/bib2html-links/Routledge15-Au.pdf

Ascone, D., Lindsey, T., & Varghese, C. (2009). An examination of driver distraction as recorded in NHTSA databases. NHTSA.

Begg, D. (2014) A 2050 vision for London: What are the implications of driverless transport. Commissioned by Clear Channel, and retrieved from: http://www.transporttimes.co.uk/Admin/uploads/64165-Transport-Times_A-2050-Vision-for- London_AWWEB-READY.pdf (October 5, 2015).

Bhat, C. R. and F. S. Koppelman (1999) "Activity-based modeling of travel demand," in *Handbook of Transportation Science*, pp. 35–61, Springer.

Bierlaire, M. (2003) BIOGEME: A free package for the estimation of discrete choice models. *Proceedings of the 3rd Swiss Transportation Research Conference*, Ascona, Switzerland.

Blumberg, M. and H. Bar-Gera (2009) "Consistent node arrival order in dynamic network loading models," *Transportation Research Part B: Methodological*, vol. 43, no. 3, pp. 285–300.

BMW Group. (2011). *The left turn assistant—turning left safely by looking out for oncoming traffic*. Retrieved from Technology, Research, Development: https://www.press.bmwgroup.com/global/pressDetail.html?title=the-left-turn-assistant-%E2%80%93-turning-left-safely-by-looking-out-for-oncoming-traffic&outputChannelId=6&id=T0108975EN&left_menu_item=node

BMW. (2012). *BMW Intelligent Headlight Technology: Long Version.* Retrieved from https://www.youtube.com/watch?v=-dvPZ3H1Vm4

Boyce, D. E., Y.-F. Zhang, and M. R. Lupa (1994) "Introducing feedback into four-step travel forecasting procedure versus equilibrium solution of combined model," *Transportation Research Record*, pp. 65–65.

Brackstone, M. and M. McDonald (1999) "Car-following: a historical review," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 2, no. 4, pp. 181–196.

Braess, D. (1968) "Uber ein paradoxon aus der verkehrsplanung," *Unternehmensforschung*, vol. 12, no. 1, pp. 258–268.

Brassfield, M. (2014). "Google to Begin Testing Self-Driving Motorcycles in California." Available at http://www.notimpossiblenow.com/the-latest/google-self-driving-motorcycles.

Bureau of Labor Statistics. (2014). "State Occupational Employment and Wage Estimates in Texas." from http://www.bls.gov/oes/current/oes_tx.htm.

Burns, L. D., W. C. Jordan, and B. A. Scarborough (2013) “Transforming personal mobility,” *The Earth Institute*.

Carlino, D., M. Depinet, P. Khandelwal, and P. Stone (2012) “Approximately orchestrated routing and transportation analyzer: Large-scale traffic simulation for autonomous vehicles,” in *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, pp. 334–339, IEEE.

Carlino, D., S. D. Boyles, and P. Stone (2013) “Auction-based autonomous intersection management,” in *Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on*, pp. 529–534, IEEE.

Carmax. (2015). *Top 10 High-Tech Car Safety Technologies*. Retrieved from 5238 http://www.carmax.com/enUS/top-10-lists/Top-10-High-Tech-Car-Safety-Technologies.html

Cars.com. (2012). *Electronic Stability Control*. Retrieved from http://www.cars.com/go/advice/Story.jsp?section=safe&subject=safe_tech&story=techStability

Casley, S. V., Jardim, A. S., and Quartulli, A. M. (2013). A Study of Public Acceptance of Autonomous Cars. Bachelor of Science thesis. Worcester Polytechnic Institute, Worcester, MA, USA. Retrieved from: http://www.wpi.edu/Pubs/E-project/Available/E-project-043013-155601/unrestricted/A_Study_of_Public_Acceptance_of_Autonomous_Cars.pdf (March 8, 2015).

Cervero, R. (2001). "Induced Demand: An Urban Metropolitan Perspective."

Childress, C., P. S. R. Council, B. Nichols, B. Charlton, and S. Coe (2014) “Using an activity-based model to explore possible impacts of automated vehicles.”

CityMobile2 (2015). "City Activities." from http://www.citymobil2.eu/en/.

Continental (2015). Continental Mobility Study 2015. Retrieved from: https://www.conti-online.com/www/download/pressportal_com_en/themes/initiatives/channel_mobility_study_en/o v_mobility_study2015_en/download_channel/mobistud2015_praesentation_en.pdf (March 7, 2015).

Cuddy, M., A. Epstein, C. Maloney, R. Westrom, J. Hassol, A. Kim, D. Damm-Luhr, and C. Bettisworth (2014) “The smart/connected city and its implications for connected transportation,” tech. rep.

Daganzo, C. F. (1995) “The cell transmission model, part ii: network traffic,” Transportation Research Part B: Methodological, vol. 29, no. 2, pp. 79–93.

Daganzo, C. F. (1995) “A finite difference approximation of the kinematic wave model of traffic flow,” *Transportation Research Part B: Methodological*, vol. 29, no. 4, pp. 261–276.

Daganzo, C. F. (1994) “The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory,” *Transportation Research Part B: Methodological*, vol. 28, no. 4, pp. 269– 287.

Daganzo, C. F. (1998) Queue spillovers in transportation networks with a route choice. *Transportation Science*, 32(1), 3-11.

Dresner, K. & Stone, P. (2008). A Multiagent Approach to Autonomous Intersection Management. *Journal of Artificial Intelligence Research*, (31), 591-656. Retrieved from http://www.cs.utexas.edu/~pstone/Papers/bib2html-links/JAIR08-dresner.pdf

Dresner, K. and P. Stone (2004) “Multiagent traffic management: A reservation-based intersection control mechanism,” in *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 2*, pp. 530–537, IEEE Computer Society.

Dresner, K. and P. Stone (2005) “Multiagent traffic management: An improved intersection control mechanism,” in *Proceedings of the fourth international joint conference on autonomous agents and multiagent systems*, pp. 471–477, ACM.

Dresner, K. and P. Stone (2006) “Multiagent traffic management: Opportunities for multiagent learning,” in *Learning and Adaption in Multi-Agent Systems*, pp. 129–138, Springer.

Dresner, K. and P. Stone (2006) “Traffic intersections of the future,” in *Proceedings of the National Conference on Artificial Intelligence*, vol. 21, p. 1593, Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press;.

Dresner, K. M. and P. Stone (2007) “Sharing the road: Autonomous vehicles meet human drivers,” in *IJCAI*, vol. 7, pp. 1263–1268.

Duthie, J. C., N. Nezamuddin, N. R. Juri, T. Rambha, C. Melson, C. M. Pool, S. Boyles, S. T. Waller, and R. Kumar (2013) “Investigating regional dynamic traffic assignment modeling for improved bottleneck analysis: Final report,” Tech. Rep. FHWA/TX-13/0-6657-1, University of Texas at Austin, Center for Transportation Research.

Elefteriadou, L., D. Torbic, and N. Webster (1997) “Development of passenger car equivalents for freeways, two- lane highways, and arterials,” *Transportation Research Record: Journal of the Transportation Research Board*, no. 1572, pp. 51–58.

Endorf, R. (2015). "The Value of Travel Time Savings: Departmental Guidance for Conduction Economic Evaluations Revisions 2."

Englund, C., et al. (2014). Cooperative speed harmonization for efficient road utilization. Communication Technologies for Vehicles (Nets4Cars-Fall), 2014 7th International Workshop on, IEEE.

Fagnant, D. & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167-181. http://dx.doi.org/10.1016/j.tra.2015.04.003

Fagnant, D. J. and K. M. Kockelman (2015) “Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles,” in *Transportation Research Board 94th Annual Meeting*, no. 15-1962.

Fagnant, D. J. and K. M. Kockelman (2014) “The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios,” *Transportation Research Part C: Emerging Technologies*, vol. 40, pp. 1–13.

Fagnant, D. J. and K. M. Kockelman (2013) "Preparing a Nation for Autonomous Vehicles." Eno Center for Transportation.

Fajardo, D., T.-C. Au, S. Waller, P. Stone, and D. Yang (2011) “Automated intersection control: Performance of future innovation versus current traffic signal control,” *Transportation Research Record: Journal of the Transportation Research Board*, no. 2259, pp. 223–232.

Fleyeh, H., & Dougherty, M. (2005). *Road and Traffic Sign Detection and Recognition.* Advanced OR and AI Methods in Transportation.

Ford Motor Corp. (2015). *Ford Mykey, now on 6 million vehicles, helps parents keep teens safe this summer.* Retrieved from https://media.ford.com/content/fordmedia/fna /us/en/news/2013/06/11/ford-mykey--now- on-6-million-vehicles--helps-parents-keep-teens-.html

Gardner, L. M., M. Duell, and S. T. Waller (2013) “A framework for evaluating the role of electric vehicles in transportation network infrastructure under travel demand variability,” *Transportation Research Part A: Policy and Practice*, vol. 49, pp. 76–90.

Gartner, N., C. J. Messer, and A. K. Rathi (2005) “Revised monograph on traffic flow theory: a state-of-the-art report,” *Special Report by the Transportation Research Board of the National Research Council*.

General Motors. (2015). *New Malibu Tech Helps Parents Teach Kids Safe Driving.* Retrieved from http://www.gm.com/article.content_pages_news_us_en_2015_mar_0320-teen-drivers.html

Google (2015). Google Self-Driving Car Project Monthly Report - September 2015. Retrieved from https://plus.google.com/+GoogleSelfDrivingCars/videos.

Greenshields, B., W. Channing, H. Miller, et al. (1935) “A study of traffic capacity,” in *Highway research board proceedings*, vol. 1935, National Research Council (USA), Highway Research Board.

Gucwa, M. (2014) Mobility and Energy Impacts of Automated Cars. Presentation to the Automated Vehicles Symposium. Burlingame, CA.

Harris, M. (2015) Uber could be First to Test Completely Driverless Cars in Public. IEEE Spectrum. September 14.

HAVEit. (2015). Retrieved from http://www.haveit-eu.org/displayITM1.asp?ITMID=6&LANG=EN

Head, L., S. Shaldover and A. Wilkey (2012) Multi-Modal Intelligent Traffic Signal System Stakeholder Input Report. University of Arizona.

Honda Motor Co. Inc. (2015). *Adaptive Cruise Control*. Retrieved from Honda: http://owners.honda.com/vehicles/information/2014/Accord-Sedan/features/Adaptive-Cruise-Control/2

Howard, B. (2013). *What is adaptive cruise control, and how does it work?* Retrieved from ExtremeTech: http://www.extremetech.com/extreme/157172-what-is-adaptive-cruise-control-and-how-does-it-work

Huang, Hai-Jun, Li, Zhi-Chun (2007) A multiclass, multicriteria logit-based traffic equilibrium assignment model under ATIS. *European Journal of Operational Research* 176.3, 1464-1477.

IIHS (2015). “Teenagers: Driving carries extra risk for them” from http://www.iihs.org/iihs/topics/t/teenagers/topicoverview.

Kim, K., G. Rousseau, J. Freedman, and J. Nicholson (2015) “The travel impact of autonomous vehicles in metro Atlanta through activity-based modeling.” Conference Slides.

Kometani, E. and T. Sasaki (1961) “Dynamic behaviour of traffic with non-linear spacing-speed relationship.”

KPMG. (2013). Self-driving cars: Are we ready? Retrieved from: http://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/self-driving-cars-are-we-ready.pdf (March 11, 2015).

Kyriakidis, M., Happee, R., and De Winter, J. (2014) Public Opinion on Automated Driving: Results of an International Questionnaire Among 5,000 Respondents. Delft University of Technology (working paper). Retrieved from: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2506579 (October 15, 2014).

LaMondia, J., D. Fagnant, H. Qu, J. Barrett, and K. Kockelman (2016) Long-Distance Travel Mode Shifts due to Automated Vehicles. Proc's of the 95th Annual Meeting of the Transportation Research Board, Washington, D.C.

Lampton, C. (2012). *How are cars making the blind spot less dangerous?* Retrieved from HowStuffWorks: http://auto.howstuffworks.com/car-driving-safety/safety-regulatory-devices/cars-making-blind-spot-less-dangerous.htm

Levin, M. & Boyles, S. (2015). Intersection Auctions and Reservation-Based Control in Dynamic Traffic Assignment. *Transportation Research Record: Journal of the Transportation Research Board*, *2497*, 35-44. http://dx.doi.org/10.3141/2497-04

Levin, M. W. and S. D. Boyles (2015a) “Effects of autonomous vehicle ownership on trip, mode, and route choice,” in *Transportation Research Board 94th Annual Meeting*, no. 15-2147.

Lighthill, M. J. and G. B. Whitham (1955) “On kinematic waves. ii. a theory of traffic flow on long crowded roads,” in *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, vol. 229, pp. 317–345, The Royal Society, 1955.

Litman, T. (2015) “Autonomous vehicle implementation predictions: Implications for transport planning,” in *Transportation Research Board 94th Annual Meeting*, no. 15-3326.

Lutin, J., Kornhauser, A., & Lerner-Lam, E. (2013). The revolutionary development of self-driving vehicles and implications for the transportation engineering profession. *ITE Journal*.

LUX Research. (2014). *Self-driving Cars an $87 Billion Opportunity in 2030, Though None Reach Full Autonomy*. Retrieved from http://www.luxresearchinc.com/news-and-events/press-releases/read/self-driving-cars-87-billion-opportunity-2030-though-none-reach

MacKenzie, D., Z. Wadud, and P. Leiby (2014). A First-order Estimate of Energy Impacts of Automated Vehicles in the United States. TRB Paper No. 14-2193, Transportation Research Board 93rd Annual Meeting. Washington, DC.

Marcotte, Patrice, Wynter, Laura (2004) A new look at the multiclass network equilibrium problem. *Transportation Science* 38 (3): 282-292.

Martin, W. A. and N. A. McGuckin (1998). Travel estimation techniques for urban planning, National Academy Press Washington, DC.

McNally, M. G. (2008) "The four step model," *Center for Activity Systems Analysis*.

MEA Forensic Engineers & Scientists. (2013). *Benefits and Complications of Electronic Stability Control (ESC).* Retrieved from MEA Forensic: http://www.meaforensic.com/forensic-engineering-expert-witness/blog/bid/102334/Benefits-and-Complications-of-Electronic-Stability-Control- ESC

Milanés, V., et al. (2011). "Automated on-ramp merging system for congested traffic situations." Intelligent Transportation Systems, IEEE Transactions on 12(2): 500-508.

Mobileye. (2015). *Traffic Sign Detection.* Retrieved from Traffic Sign Detection: http://www.mobileye.com/technology/applications/traffic-sign-detection/

Musti, S., and Kockelman, K. M. (2011) Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. *Transportation Research Part A: Policy and Practice*, 45(8): 707-720.

Nagurney, A., J. Dong, and D. Zhang (2002) "A supply chain network equilibrium model," *Transportation Research Part E: Logistics and Transportation Review*, vol. 38, no. 5, pp. 281–303.

Newell, G. F. (2002) "A simplified car-following theory: a lower order model," *Transportation Research Part B: Methodological*, vol. 36, no. 3, pp. 195–205.

Newell, G. F. (1993) "A simplified theory of kinematic waves in highway traffic, part i: General theory," *Transportation Research Part B: Methodological*, vol. 27, no. 4, pp. 281–287.

National Highway Traffic Safety Administration (NHTSA) (2008) "National Motor Vehicle Crash Causation Survey Report to Congress." National Highway Traffic Safety Administration Technical Report DOT HS 811: 059.

NHTSA (2013) Preliminary Statement of Policy Concerning Automated Vehicles. Dept. of Transportation.

NHTSA (2014) From http://www.nhtsa.gov/About+NHTSA/Press+Releases/NHTSA-issues-advanced-notice-of-proposed-rulemaking-on-V2V-communications.

NHTSA (2015) "Fatality Analysis Reporting System." from http://www-fars.nhtsa.dot.gov/Main/index.aspx.

NHTSA (2008) National Motor Vehicle Crash Causation Survey. U.S. Department of Transportation, Report DOT HS 811 059. Retrieved from: http://www-nrd.nhtsa.dot.gov/Pubs/811059.PDF (October 15, 2014).

NHTSA (2013) Preliminary statement of policy concerning automated vehicles. Washington, D.C. Retrieved from: http://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf (October 15, 2014).

NHTSA (2014) U.S. Department of Transportation announces decision to move forward with vehicle-to-vehicle communication technology for light vehicles. Washington, D.C. Retrieved from: http://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf http://www.nhtsa.gov/About+NHTSA/Press+Releases/2014/USDOT+to+Move+Forward+with+ Vehicle-to-Vehicle+Communication+Technology+for+Light+Vehicles (October 15, 2014).

NHTSA (2010) *Crash Factors in Intersection-Related Crashes: An On-Scene Perspective*. Washington, D.C. Retrieved from https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811366

NHTSA (2013) Preliminary Statement of Policy Concerning Automated Vehicles. NHTSA. (2014). Notice and NHTSA report outline promise of cutting-edge technology.

NSC (2012) Estimating the Costs of Unintentional Injuries, 2012. N. S. Council.

Paul, B. M., Kockelman, K. M., and Musti, S. (2011) The light-duty-vehicle fleet's evolution: anticipating PHEV adoption and greenhouse gas emissions across the US fleet (No. SWUTC/11/161023-1).

Petersen, E. and P. Vovsha (2006) "Intrahousehold car-type choice for different travel needs," *Transportation Research Record: Journal of the Transportation Research Board*, no. 1985, pp. 207-219.

Pinjari, A. R., B. Augustin, and N. Menon (2013) "Highway capacity impacts of autonomous vehicles: An assessment," Tech. Rep., University of South Florida, Department of Civil and Environmental Engineering.

Powell, W. B. and Y. Sheffi (1982) "The convergence of equilibrium algorithms with predetermined step sizes," *Transportation Science*, vol. 16, no. 1, pp. 45–55.

PUMS (Public Use Microdata Sample) (2013). United State Census Bureau: American Community Survey. Retrieved from: http://www.census.gov/acs/www/data_documentation/pums_data (October 15, 2014).

Qian, X., J. Gregoire, F. Moutarde, and A. De La Fortelle (2014) "Priority-based coordination of autonomous and legacy vehicles at intersection," in *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, pp. 1166–1171, IEEE.

Rakha, H., K. Ahn, and K. Moran (2012) "Integration framework for modeling eco-routing strategies: logic and preliminary results," *International Journal of Transportation Science and Technology*, vol. 1, no. 3, pp. 259–274.

Richards, P. I. (1956) "Shock waves on the highway," *Operations research*, vol. 4, no. 1, pp. 42–51.

Robbins, H. and S. Monro (1951) "A stochastic approximation method," *The annals of mathematical statistics*, pp. 400–407.

SAE (2014). *SAE International Technical Standard Provides Terminology for Motor Vehicle Automated Driving Systems*. (SAE International) Retrieved 4 6, 2015, from http://www.sae.org/servlets/pressRoom?OBJECT_TYPE=PressReleases&PAGE=showRelease&RELEASE_ID=2715

Schakel, W. J., B. Van Arem, and B. D. Netten (2010) "Effects of cooperative adaptive cruise control on traffic flow stability," in *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, pp. 759–764, IEEE.

Schepperle, H. and K. Bohm (2007) "Agent-based traffic control using auctions," in *Cooperative Information Agents XI*, pp. 119–133, Springer.

Schepperle, H., K. Bohm, and S. Forster (2008) "Traffic management based on negotiations between vehicles– a feasibility demonstration using agents," in *Agent-Mediated Electronic Commerce and Trading Agent Design and Analysis*, pp. 90–104, Springer.

Schoettle, B, and Sivak, M. (2014b) A survey of public opinion about connected vehicles in the U.S., the U.K., and Australia. University of Michigan, Technical Report No. UMTRI-2014-10. Retrieved from: http://deepblue.lib.umich.edu/bitstream/handle/2027.42/106590/102996.pdf?sequence=1 (October 15, 2014).

Schoettle, B., and Sivak, M. (2014a) A survey of public opinion about autonomous and self-driving vehicles in the US, the UK, and Australia. University of Michigan, Technical Report No. UMTRI-2014-21. Retrieved from: http://deepblue.lib.umich.edu/bitstream/handle/2027.42/108384/103024.pdf?sequence=1&isAllo wed=y (October 15, 2014).

Schrank, D., Eisele, B., Lomax, T., & Bak, J. (2015) *2015 Urban Mobility Scorecard*. College Station, Texas: Texas A&M Transportation Institute. Retrieved from http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-scorecard-2015.pdf

Seapine Software (2014) Study finds 88% of adults would be worried about riding in a driverless car. Retrieved from: http://www.seapine.com/pr.php?id=217 (March 10, 2015). Smiechowski J. (2014) Google's driverless prototype is ready to hit the road. Retrieved from: http://www.hybridcars.com/googles-driverless-prototype-is-ready-to-hit-the-road/ (April 25, 2015).

Sheffi, Y. (1985) "Urban transportation network," Equilibrium analysis with mathematical programming methods, Prentice Hall.

Shladover, S., Su, D., & Lu, X. (2012) Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow. *Transportation Research Record: Journal of the Transportation Research Board*, *2324*, 63-70. http://dx.doi.org/10.3141/2324-08

Sivinksi, R. (2011) *Crash Prevention Effectiveness of Light-Vehicle Electronic Stability Control: An Update of the 2007 NHTSA Evaluation.* Washington, DC: National Highway Traffic Safety Administration. Retrieved from http://www-nrd.nhtsa.dot.gov/Pubs/811486.pdf

Smith, B. W. (2012) "Managing autonomous transportation demand," *Santa Clara Law Review*, vol. 52, no. 4.

Soniak, M. (2012). "When and Where Was the First Car Accident?". Available at http://mentalfloss.com/article/31807/when-and-where-was-first-car-accident.

Spieser, K., K. Treleaven, R. Zhang, E. Frazzoli, D. Morton, and M. Pavone (2014) "Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore," in *Road Vehicle Automation*, pp. 229–245, Springer.

Strauss, Matthias, et al. (2010) Automated Assistance in Roadworks and Congestion: 1st System Functionality. http://www.haveit-eu.org/LH2Uploads/ItemsContent/24/HAVEit_212154_D51.3_Public.pdf

Tampère, C. M., R. Corthout, D. Cattrysse, and L. H. Immers (2011) "A generic class of first order node models for dynamic macroscopic simulation of traffic flows," *Transportation Research Part B: Methodological*, vol. 45, no. 1, pp. 289–309.

Tawari, A., Martin, S., & Trivedi, M. M. (2014) Continuous Head Movement Estimator for Driver Assistance: Issues, Algorithms, and On-Road Evaluations. *IEEE Transactions on Intelligent Transportation Systems*, 1-13.

Texas A&M Transportation Institute (2015) Texas' Most Congested Roadways 2015. Retrieved 5 July 2016, from http://mobility.tamu.edu/texas-most-congested-roadways/

Texas Department of Transportation (TxDOT) (2015) 100 Congested Roadways. Inside TxDOT Projects.<http://www.txdot.gov/inside-txdot/projects/100-congested-roadways.html>.

TxDOT (2014) Texas Motor Vehicle Crash Statistics - 2014.

Tientrakool, P., Y.-C. Ho, and N. F. Maxemchuk (2011) "Highway capacity benefits from using vehicle-to- vehicle communication and sensors for collision avoidance," in *Vehicular Technology Conference (VTC Fall), 2011 IEEE*, pp. 1–5, IEEE.

Toyota Motor Corp. (2015) *Lane Keeping Assist*. Retrieved from Safety Technology: http://www.toyota-global.com/innovation/safety_technology/safety_technology/technology_file/active/lka.html

Travers, J. (2008) *Ignorance is BLIS*. Retrieved from Consumer Reports: http://www.consumerreports.org/cro/news/2008/03/ignorance-is-blis/index.htm?loginMethod=auto&copyrightYear=2013

Tuerprasert, K. and C. Aswakul (2010) "Multi-class cell transmission model for heterogeneous mobility in general topology of road network," *Journal of Intelligent Transportation Systems*, vol. 14, no. 2, pp. 68– 82.

Tung, R., Z. Wang, and Y.-C. Chiu (2010) "Integration of dynamic traffic assignment in a four step model framework a deployment case study in Seattle model," in *Proc., Third Conference on Innovations in Travel Modeling*.

Underwood, S. E. (2014) Automated vehicles forecast vehicle symposium opinion survey. Presented at the Automated Vehicles Symposium 2014, San Francisco, CA. Retrieved from: https://drive.google.com/file/d/0B8gGx-CYkV-wREVMTEhHQUxjOWM/edit. (March 10, 2015).

US Department of Transportation (USDOT) (2015) Connected Vehicle Pilot Deployment Program. Available at http://www.its.dot.gov/pilots/cv_pilot_plan.htm.

USDOT (2015) Frequently Asked Questions re. Connected Vehicles. Available at http://www.its.dot.gov/connected_vehicle/connected_vehicles_FAQs.htm.

USDOT ITS JPO. (2015) *Connected Vehicle Safety Pilot*. Retrieved from http://www.its.dot.gov/research.htm

US Environmental Protection Agency (2009) “Motor vehicle emission simulator,” Tech. Rep. EPA-420-B-09-041, Office of Transportation and Air Quality.

Vallet, M. (2013) Survey: Drivers ready to trust robot cars? Retrieved from: http://www.carinsurance.com/Articles/autonomous-cars-ready.aspx (March 10, 2015).

Van Aerde, M. and H. Rakha (1995) “Multivariate calibration of single regime speed-flow-density relationships,” in *Proceedings of the 6th 1995 Vehicle Navigation and Information Systems Conference*, pp. 334–341.

Van Arem, B., et al. (2006) "The Impact of Cooperative Adaptive Cruise Control on Traffic-Flow Characteristics." Intelligent Transportation Systems, IEEE Transactions on 7(4): 429-436.

Vasirani, M. and S. Ossowski (2010) “A market-based approach to accommodate user preferences in reservation- based traffic management,” tech. rep., Technical Report ATT.

Vasirani, M. and S. Ossowski (2012) “A market-inspired approach for intersection management in urban road traffic networks,” *Journal of Artificial Intelligence Research*, pp. 621–659.

Wardrop, J. G. (1952) “Road paper some theoretical aspects of road traffic research,” in *ICE Proceedings: Engineering Divisions*, vol. 1, pp. 325–362, Thomas Telford.

Wired.com. (2013). Retrieved from http://www.wired.com/2013/01/ces-2013-audi-self-parking/
Wu, J., Subramanian, R., Craig, M., Starnes, M., & Longthorne, A. (2013). The effect of earlier or automatic collision notification on traffic mortality by survival analysis. *Traffic injury prevention*, 50-57.

Xu, Q., K. Hedrick, R. Sengupta, and J. VanderWerf (2002) “Effects of vehicle-vehicle/roadside-vehicle communication on adaptive cruise controlled highway systems,” in *Vehicular Technology Conference, 2002. Proceedings. VTC 2002-Fall. 2002 IEEE 56th*, vol. 2, pp. 1249–1253, IEEE.

Yang, Hai, Hoi Yan Kong, and Meng, Qiang (2001) Value-of-time distributions and competitive bus services. *Transportation Research Part E: Logistics and Transportation Review* 37.6, 411-424.

Yperman, I. (2007) “The link transmission model for dynamic network loading,” Katholieke Universiteit Leuven.

Yperman, I., S. Logghe, and B. Immers (2005) “The link transmission model: An efficient implementation of the kinematic wave theory in traffic networks,” in *Proceedings of the 10th EWGT Meeting*.

Zachariah, J. et al. (2014) Uncongested Mobility for All: A Proposal for an Area-Wide Autonomous Taxi System in New Jersey. Proceedings of the Transportation Research Board 93rd Annual Meeting. Washington, D.C.

Zhang, W., S. Guhathakurta, J. Fang, and G. Zhang (2015) “Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach,” *Sustainable Cities and Society*, vol. 19, pp. 34–45.

Zhu, F. and S. V. Ukkusuri (2015) “A linear programming formulation for autonomous intersection control within a dynamic traffic assignment and connected vehicle environment,” *Transportation Research Part C: Emerging Technologies*, vol. 55, pp. 363–378.

# Appendix A: Identified Testbeds for Testing CAV Applications

**Table A-1: Suggested Roadways for Preliminary CAV Light-Duty Vehicle Platooning Testing (Source: TTI, 2015)**

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Bexar | Blanco Rd / FM 2696 | Charles West Anderson Loop / SL 1604 N | Connally Loop N / IH 410 | 6.64 | 59,567 |
| Dallas | W Illinois Ave | SS 408 | R L Thornton Fwy / IH 35E / US 77 | 5.30 | 58,520 |
| Tarrant | FM 1709 | Main St / US 377 | Northwest Hwy / SH 114 | 9.04 | 58,510 |
| Bexar | Wurzbach | Blanco Rd / FM 2696 | Connally Loop W /IH 410 / SH16 | 9.86 | 58,459 |
| Bexar | Potranco Rd / FM 1957 | Talley Rd | Raymond E. Stotzer Jr Fwy / SH 151 | 7.21 | 58,322 |
| Dallas | Josey Ln | President George Bush Turnpike Toll Rd | Lyndon B Johnson / IH 635 | 5.30 | 58,216 |
| Harris | Tomball Pkwy / SH 249 | Holderrieth Rd | Perry Rd | 7.05 | 57,981 |
| Tarrant | E Loop 820 S / IH 820 | Tom Landry Fwy / IH 30 | IH 20 | 6.82 | 57,723 |
| Harris | Gessner | Northwest Fwy / US 290 | Katy Fwy / IH10/ US90 | 5.78 | 56,895 |
| Harris | Bissonnet St | Southwest Fwy / IH 69/ US 59 | West Loop S/ IH 610 | 6.69 | 56,236 |
| Harris | FM 1960 | North Fwy / IH 45 | Eastex Fwy / US 59 | 10.10 | 55,629 |
| Harris | East Fwy / IH 10 | E Sam Houston Pkwy /SL 8 | SS 330 | 5.76 | 55,191 |
| Dallas | S SL 12 W | SS 408 (W Illinois Ave) | R.L. Thornton Fwy / IH 35E /US 77 | 9.75 | 54,747 |
| Bexar | Pleasanton | S Flores Street | Connally Loop S / IH 410 | 5.14 | 53,873 |
| Harris | Fairbanks N Houston | N Sam Houston Pkwy W / SL8 | Northwest Fwy / US 290 | 5.27 | 53,302 |
| Bexar | FM 471 | Charles West Anderson Loop / SL 1604 NW | Bandera Rd / SH 16 | 6.01 | 52,996 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Dallas | John W. Carpenter Fwy / SH 114 | President George Bush Turnpike Toll Rd | Airport Fwy / SH 183 | 6.04 | 52,824 |
| Harris | Bellaire Blvd | Addicks-Clodine | W Sam Houston Pkwy / SL 8 | 6.88 | 51,692 |
| Travis | RM 620 | RM 2222 | SH 71 | 12.86 | 51,323 |
| Dallas | IH 20 | Marvin D Love Fwy / US 67 | S Central Expy / SH 310 | 9.09 | 51,036 |
| Bexar | Culebra Rd | Connally Loop W / IH 410 | Bandera Rd / SS 421 | 5.57 | 50,446 |
| El Paso | Montana Ave / US 180 / US 62 | Gateway Blvd / IH 10 | Global Reach Dr | 5.39 | 50,387 |
| Dallas | S Buckner Blvd / SL 12 E | E R L Thornton Fwy / IH 30 / US 67 | C F Hawn Fwy / US 175 | 5.92 | 50,289 |
| Dallas | Harry Hines Blvd | W Northwest Hwy / SL 12 N | Dallas North Tollway | 5.80 | 49,902 |
| Dallas | Tom Landry Fwy / IH 30 | SH 360 | S Walton Walker Blvd / SL 12 W | 8.71 | 49,800 |
| Bexar | Military Dr / SL 13 | S PanAm Expy / IH 35 / IH10 | Goliad Rd | 5.96 | 49,489 |
| Harris | N Fry Rd | FM 529 | Katy Fwy / IH 10 / US 90 | 6.60 | 49,377 |
| Dallas | N Buckner Blvd / SL 12 E | E Northwest Hwy / SL 12 N | E R L Thornton Fwy / IH 30 / US 67 | 5.01 | 49,128 |
| Travis | N Lamar Blvd / SL 275 | IH 35 | US 183 | 5.99 | 49,092 |
| Bexar | Charles West Anderson Loop / SL 1604 N | US 281 | IH 35 | 9.42 | 48,960 |
| Tarrant | University Dr | Jacksboro Hwy / SH 199 | Granbury Rd | 5.30 | 48,728 |
| Harris | FM 1960 | Eastex Fwy / US 59 | Crosby Huffman Rd / FM 2100 | 11.07 | 48,536 |
| Travis | SH 71 | RM 620 | US 290 | 7.25 | 48,529 |
| Dallas | Forest Lane | Lyndon B Johnson / IH 635 (Grissom Ln) | SH 75 | 10.87 | 48,324 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Harris | Beechnut Blvd | W Sam Houston Pkwy S / SL 8 | West Loop S/ IH 610 | 6.10 | 48,023 |
| Bexar | Huebner Rd | Charles West Anderson Loop / SL 1604 N | Bandera Rd / SH 16 | 9.89 | 47,717 |
| Dallas | Belt Line Rd | Dallas North Tollway | US 75 | 5.24 | 47,482 |
| Harris | Murphy Rd / FM 1092 | Southwest Fwy / US 59 | SH 6 | 5.99 | 47,218 |
| Dallas | Lyndon B Johnson / IH 635 | US 80 | IH 20 | 6.73 | 47,058 |
| Bexar | Charles West Anderson Loop / SL 1604 NE | FM 1976 | IH 10 / US 90 | 5.06 | 46,890 |
| Harris | Westheimer Rd / Elgin St | West Loop S/ IH 610 | Southwest Fwy / US 59 | 5.58 | 46,414 |
| Dallas | Cockrell Hill Rd | Tom Landry Fwy / IH 30 | S G Alexander Fwy / US 67 | 8.70 | 46,397 |
| Harris | East Fwy / IH 10 | E Loop Fwy / IH 610 | E Sam Houston Pkwy /SL 8 | 7.42 | 46,281 |
| Harris | FM 2234 | S Sam Houston Pkwy W /SL 8 | Blueridge Rd | 6.40 | 46,130 |
| Dallas | Belt Line Rd | Stemmons Fwy / IH 35E/ US 77 | Dallas North Tollway | 5.13 | 45,702 |
| Bexar | Callaghan Rd | McDermott Fwy / IH 10 / US 87 | Raymond E. Stotzer Jr Fwy / SH 151 | 7.45 | 45,552 |
| Harris | Holcombe Blvd | West Loop S/ IH 610 | South Fwy / SH 288 | 5.32 | 45,043 |
| Tarrant | SH 183 | Jacksboro Hwy / SH 199 | IH 30 | 5.10 | 44,379 |
| Dallas | Ferguson Rd | Lyndon B Johnson Fwy / IH 635 | Samuell Blvd | 6.35 | 43,961 |
| Bexar | Babcock Rd | Charles West Anderson Loop / SL 1604 NW | Fredericksburg Rd / SL 345 | 11.12 | 43,903 |
| Harris | Briar Forest Dr_San Felipe St | W Sam Houston Pkwy / SL 8 | West Loop S/ IH 610 | 6.31 | 43,805 |
| Harris | Clay Rd | Barker Cypress Rd | W Sam Houston Pkwy N / SL 8 | 7.49 | 43,573 |
| Harris | FM 2920 | SH 249 | Kuykendahl Rd | 8.37 | 43,230 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Bexar | Vance Jackson | Huebner Road | Fredericksburg Rd / SL 345 | 6.38 | 42,890 |
| Harris | Eldridge Pkwy | Katy Fwy / IH 10/US 90 | Westpark Tollway | 5.09 | 42,887 |
| Travis | S Mopac Expwy / SL1 | S Capital of Texas Hwy / SL 360 | SH 45 | 7.40 | 42,885 |
| Dallas | Royal Ln | Stemmons Fwy / IH 35E/ US 77 | US 75 | 7.58 | 42,477 |
| Bexar | Bitters Rd | Charles West Anderson Loop / SL 1604 N | Starcrest Drive | 6.00 | 42,456 |
| Harris | Spencer Rd / FM 529 | Stockdick School Road | SH 6 | 7.17 | 42,304 |
| Bexar | Bandera Rd / SH 421 | Connally Loop NW / IH 410 | McDermott Fwy / IH 10 / US 87 | 6.00 | 42,182 |
| Harris | Spencer Hwy | Texas St | Red Bluff Rd | 6.12 | 42,012 |
| Travis | SH 71 | IH 35 | SH 130 / SH 45 | 8.25 | 41,364 |
| Tarrant | Jacksboro Hwy / SH 199 | NW Loop 820 / IH 820 | W Lancaster Ave | 6.56 | 41,067 |
| El Paso | Alameda Ave / SH 20 | North Carolina Dr | S Americas Ave / SL 375 | 7.12 | 41,012 |
| Tarrant | Wilshire Blvd / SH 174 | IH 35W | E 12th St / FM 917 | 7.73 | 40,837 |
| Harris | Jones Rd | Grant Rd | Northwest Fwy / US 290 | 5.25 | 40,791 |
| Dallas | Lemmon Ave | W Northwest Hwy / SL 12 N | N Haskell Road | 5.85 | 40,775 |
| Tarrant | SH 183 | IH 30 | IH 20 | 5.06 | 40,720 |
| Harris | Edgebrook Dr_Fairmont Pkwy | Almeda Genoa Rd | East Sam Houston Pkwy S/ SL 8 | 6.49 | 40,569 |
| Bexar | Harry Wurzbach Rd _ Burr Rd | Connally Loop N / IH 410 | Broadway St / SL 368 | 5.66 | 40,542 |
| Tarrant | BU 287 P | Old Decatur Rd | Northeast Loop 820 / IH 820 | 5.36 | 40,481 |
| Harris | Wallisville Road | Lockwood Dr | Crosby Fwy / US 90 | 5.79 | 39,664 |
| Bexar | Stone Oak Parkway | US 281 | Charles West Anderson Loop / SL 1604 N | 5.03 | 39,375 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Bexar | Jose Lopez Fwy / IH 10 / US 90 | Staff Sergeant William J.Bordelon Fwy / IH 37 / US 281 | Connally Loop E /IH 410 | 6.37 | 39,200 |
| Travis | RM 2222 | RM 620 N | N Capital of Texas Hwy / SL 360 | 5.27 | 39,187 |
| Tarrant | Davis Blvd / FM 1938 | Northwest Hwy / SH 114 | Starnes Rd | 7.65 | 39,032 |
| El Paso | SH 20 | Talbot Ave / SL 375 | Canam Hwy / IH 10/ US 180 | 5.36 | 38,982 |
| Tarrant | US 377 | IH 30 | IH 20 | 5.05 | 38,832 |
| Dallas | Spring Valley Rd | Marsh Ln | S Coit Rd | 8.93 | 38,825 |
| Harris | Weslayan St _ Stella Link Rd | Inwood Dr | S Main St /UA 90 | 6.10 | 38,652 |
| Harris | Bay Area Blvd | Gulf Fwy / IH 45 | Red Bluff Rd | 6.65 | 38,634 |
| Dallas | SH 78 | FM 544 | President George Bush Turnpike Toll Rd | 5.88 | 38,166 |
| Harris | Tidwell Rd | Eastex Fwy / US 59 | Greens Bayou | 6.27 | 37,633 |
| Bexar | Blanco Rd | Connally Loop N / IH 410 | Fredericksburg Rd / SL 345 | 5.14 | 37,633 |
| Dallas | Riverside Dr _ O'Conner Blvd | IH 635 | W Irving Blvd / SH 365 | 7.47 | 37,426 |
| Dallas | FM 1382 | IH 20 | E Belt Line Rd (Cannady Dr) | 6.52 | 37,151 |
| Harris | Memorial Dr | W Loop N Fwy / IH610 | Gulf Fwy / IH 45 | 5.09 | 36,885 |
| Dallas | Singleton Blvd | S Walton Walker Blvd / SL 12 W | N Beckley Ave | 5.32 | 36,776 |
| Dallas | Arapaho Rd | Surveyor Blvd | US 75 | 7.16 | 36,488 |
| Dallas | US 67 | IH 20 | W Belt Line Rd | 5.43 | 36,451 |
| Harris | Hillcroft Ave | Southwest Fwy / IH 69/ US 59 | S Main St /UA 90 | 6.94 | 36,282 |
| Harris | Wirt Rd_Chimney Rock Rd | Kempwood Dr | Southwest Fwy / IH 69 / US 59 | 6.44 | 36,238 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Travis | FM 969 | Ed Bluestein Blvd / US 183 | Hound Dog Trail | 5.52 | 36,040 |
| El Paso | N Loop Dr / FM 76 | North Carolina Dr | N Americas Ave / SL 375 | 5.13 | 35,858 |
| Harris | Kuykendahl Rd | FM 2920 | North Fwy / IH 45 | 9.91 | 35,659 |
| Dallas | Belt Line Rd | US 75 | N Glenbrook Dr | 5.68 | 35,301 |
| Harris | Montrose Blvd | N Main St | Main St | 5.75 | 35,292 |
| Harris | Hardy Toll Road | Cypress Creek Pkwy / FM 1960 | Aldine Bender Rd /FM 525 | 7.32 | 34,967 |
| Dallas | Campbell Rd | Preston Rd | US 75 | 5.36 | 34,945 |
| Bexar | West Fwy / IH 30 | W Loop 820 S / IH 820 | Camp Bowie Blvd / US 377 | 7.55 | 34,660 |
| Tarrant | Blue Mound Rd / FM 156 | US 81 / US 287 | Meacham Blvd | 6.23 | 34,593 |
| Harris | Beechnut St | Winkleman Dr | W Sam Houston Pkwy S / SL 8 | 5.59 | 34,478 |
| Harris | Fairmont Pkwy | East Sam Houston Pkwy S / SL 8 | Park Dr | 8.60 | 34,453 |
| Harris | E Little York Rd | North Fwy / IH 45 | Mesa Dr | 8.74 | 34,328 |
| Harris | Antoine Dr | North Sam Houston Pkwy W / SL 8 | Victory Dr | 5.03 | 34,091 |
| Dallas | Belt Line Rd / FM 1382 | E Main St / SH 180 | IH 20 | 12.39 | 34,090 |
| Bexar | Raymond E. Stotzer Jr Fwy / SH 151 | Charles West Anderson Loop W / SL 1604 | Connally Loop W /IH 410 | 5.54 | 33,965 |
| Harris | North Houston Rd | N Sam Houston Pkwy / SL 8 | Northwest Fwy / US 290 | 7.18 | 33,962 |
| Dallas | Greenville Ave | Belt Line Road / Main St | Northwest Hwy / SL 12 N | 6.20 | 33,760 |
| Bexar | NW Military Hwy / FM 1535 | Charles West Anderson / FM 1604 | Connally Loop N / IH 410 | 6.32 | 33,759 |
| Harris | S Braeswood Blvd | Bissonnet St | West Loop S/ IH 610 | 5.22 | 33,145 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Harris | W Little York Rd | N Fry Rd | Hempstead Hwy | 10.35 | 32,999 |
| Harris | Dairy Ashford | N Eldridge Pkwy | Aleif Clodine Road | 5.75 | 32,892 |
| Tarrant | Denton Hwy / US 377 | Alliance Gateway Fwy / SH 170 | Northeast Loop 820 / IH 820 | 10.36 | 32,883 |
| Harris | Greens Rd | Hardy Toll Rd | Eastex Fwy / US 59 | 5.75 | 32,696 |
| Harris | Briar Forest Dr | SH 6 | W Sam Houston Pkwy S / SL 8 | 5.39 | 32,571 |
| Harris | Gulf Fwy / IH 45 | Nasa Pkwy / FM 528 | FM 517 | 6.42 | 32,495 |
| Harris | Beaumont Hwy / BU 90 | N Sam Houston Pkwy E / SL8 | N Loop E Fwy / IH 610 | 6.29 | 32,301 |
| Harris | Aldine Bender Rd / FM 525 | North Fwy / IH 45 | Eastex Fwy / US 59 | 7.03 | 32,004 |
| Dallas | N Jim Miller Road | Highland Road | Great Trinity Forest / SL 12 S | 5.72 | 31,735 |
| Harris | Richey St / SH3 | Shaver St | Gulf Fwy / IH 45 | 5.53 | 31,593 |
| Bexar | Thousand Oaks Dr | US 281 | N PanAm Expy / IH 35 | 6.82 | 31,501 |
| Harris | Spencer Hwy | Red Bluff Rd | Broadway St | 6.82 | 31,253 |
| Dallas | MacArthur Blvd | W Grauwyler Rd | E Main St / SH 180 | 5.52 | 31,163 |
| Harris | West Lake Houston Pkwy | FM 1960 | North Sam Houston Pkwy E / SL 8 | 6.65 | 31,050 |
| Tarrant | Grapevine Hwy / SH 26 | Glade Rd | Denton Hwy / US 377 | 8.48 | 30,788 |
| Tarrant | Matlock Rd | W Sublett Rd | E Broad St | 5.58 | 30,692 |
| Harris | Richmond Ave | W Sam Houston Pkwy / SL 8 | West Loop S/ IH 610 | 5.93 | 30,657 |
| Dallas | Irving Blvd / SH 356 | Airport Fwy / SH 183 | Walton Walker Blvd / SL 12 W | 5.35 | 30,545 |
| Dallas | Ledbetter Dr / SL 12 S | R.L. Thornton Fwy / IH 35E /US 77 | C F Hawn Fwy / US 175 | 8.71 | 30,455 |
| Harris | Gessner | Katy Fwy / IH10/ US90 | Southwest Fwy / IH 69/ US 59 | 6.95 | 30,415 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Dallas | Walnut St | Lyndon B Johnson Fwy / IH 635 | N Country Club Rd | 8.38 | 30,246 |
| Harris | Fulton St | Parker Rd | Hogan St | 6.13 | 30,017 |

**Table A-2: Suggested Roadways for Intermediate CAV Light-Duty Vehicle Platooning Testing (Source: TTI, 2015)**

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Harris | SH 6 | Northwest Fwy / US 290 | Katy Fwy / IH10/ US90 | 10.00 | 97,860 |
| Tarrant | IH 30 / US 377 | Camp Bowie Blvd / US 377 | IH 35 W | 5.08 | 97,136 |
| Harris | North Sam Houston Pkwy E/ SL 8 | Hardy Toll Rd | Old Humble Rd | 6.48 | 96,194 |
| Harris | SH 6 | Katy Fwy / IH10/ US90 | Westpark Tollway | 5.40 | 93,105 |
| Dallas | President George Bush Turnpike / SH 161 | Lyndon B Johnson / IH 635 | Airport Fwy / SH 183 | 7.13 | 92,717 |
| Harris | W Sam Houston Pkwy N /SL 8 | Tomball Pkwy / SH 249 | Northwest Fwy / US 290 | 6.41 | 89,596 |
| Bexar | Bandera Rd / SH 16 | FM 1560 | Connally Loop NW / IH 410 | 7.43 | 87,984 |
| Dallas | IH 20 | SH 360 | Marvin D Love Fwy / US 67 | 11.13 | 87,376 |
| Harris | Bellaire Blvd | W Sam Houston Pkwy / SL 8 | West Loop S/ IH 610 | 5.91 | 83,803 |
| Bexar | McDermott Fwy / IH 10 / US 87 | Connally Loop N / IH 410 | S PanAm Expy / IH 35 | 6.52 | 83,552 |
| Bexar | N PanAm Expy / IH 35 | McAllister Fwy / US 281 | Connally Loop NE / IH 410 | 5.55 | 83,356 |
| Tarrant | IH 20 | US 287 | SH 360 | 9.04 | 81,699 |
| Bexar | White Rd / SL 13 | Connally Loop E / IH 410 | Rigsby Ave / US 87 | 8.20 | 80,308 |
| Harris | Eastex Fwy / IH 69 / US 59 | Little York Rd | North Sam Houston Pkwy E / SL 8 | 5.24 | 79,707 |
| Bexar | Connally Loop NE / IH 410 | N PanAm Expy / IH 35 | Rigsby Ave / US 87 | 5.57 | 79,441 |
| Dallas | Mockingbird Ln | John W. Carpenter Fwy / SH 183 | SH 75 | 5.87 | 78,673 |
| Harris | Tomball Pkwy / SH 249 | North Sam Houston Pkwy W / SL 8 | North Fwy / IH 45 | 6.92 | 78,577 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Bexar | IH10 / US 87 | Boerne Stage Rd | Charles West Anderson Loop / SL 1604 N | 6.48 | 78,338 |
| Tarrant | IH 20 | IH 35 W | US 287 | 6.46 | 76,508 |
| Tarrant | Tom Landry Fwy / IH 30 | IH 35 W | E Loop 820 / IH 820 | 6.31 | 76,181 |
| Dallas | Preston Rd / SH 289 | Sam Rayburn Tollway / SH 121 | IH 635 | 12.12 | 73,043 |
| Travis | Capital of Texas Hwy / SL 360 | RM 2222 | RM 2244 | 5.15 | 72,567 |
| Harris | Pasadena Fwy / SS 225 | E Loop Fwy / IH 610 | East Sam Houston Pkwy S/ SL 8 | 7.97 | 72,075 |
| Harris | S Post Oak Rd | S Loop W Fwy / IH610 | FM 2234 | 7.22 | 71,887 |
| Tarrant | Cooper St / FM 157 | IH 20 | BU 287P | 6.83 | 70,100 |
| Dallas | IH 30 / US 67 | Buckner Blvd / SL 12 E | President George Bush Hwy | 9.10 | 69,978 |
| Tarrant | IH 35 W | IH 20 | NE Wilshire Blvd / SH 174 | 7.94 | 69,943 |
| Harris | S Main St / UA 90 | S Loop W Fwy / IH610 | South Sam Houston Pkwy W / SL 8 | 6.54 | 69,436 |
| Dallas | Northwest Hwy / SL 12 N | Dallas North Tollway | N Buckner Blvd / SL 12 E | 5.70 | 69,393 |
| Dallas | Coit Rd | Frankford Rd | Forest Lane | 6.10 | 69,088 |
| Dallas | SH 114 | Texan Trail / SH 26 | President George Bush Turnpike Toll Rd | 6.09 | 68,995 |
| Tarrant | Collins St / FM 157 | Airport Fwy / SH 183 | Tom Landry Fwy / IH 30 | 6.88 | 68,063 |
| Harris | N Loop E Fwy / IH 610 | North Fwy / IH 45 | East Fwy / IH 10 | 8.02 | 67,585 |
| Dallas | Hampton Rd | Tom Landry Fwy / IH 30 | Marvin D Love Fwy / US 67 | 5.90 | 67,470 |
| Dallas | W Northwest Hwy / SL 12 N | Walton Walker Blvd / SL 12 W | Dallas North Tollway | 5.57 | 67,237 |
| Bexar | Rittman _ N Foster Rd | N PanAm Expy / IH 35 / IH 410 | IH 10 / US 90 | 5.05 | 66,453 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| El Paso | N Mesa St / SH 20 | Canam Hwy / IH 10 / US 180 / US 85 | Executive Center Blvd | 5.35 | 66,180 |
| Bexar | Marbach Rd | Charles West Anderson Loop W / SL 1604 | Pinn Rd | 5.59 | 65,531 |
| Dallas | Belt Line Rd | Denton Tap | Airport Fwy / SH 183 | 7.67 | 64,251 |
| Dallas | Lyndon B Johnson / IH 635 | SH 121 | Stemmons Fwy / IH 35 E / US 77 | 9.24 | 64,048 |
| Bexar | San Pedro Ave / SS 537 | Connally Loop N / IH 410 | S PanAm Expy / IH 35 | 5.92 | 63,643 |
| Dallas | Belt Line Rd | Airport Fwy / SH 183 | E Main St / SH 180 | 6.25 | 61,833 |
| Harris | Bissonnet St | Clodine Rd | Southwest Fwy / IH 69/ US 59 | 7.38 | 61,581 |

**Table A-3: Suggested Roadways for Advanced CAV Light-Duty Vehicle Platooning Testing (Source: TTI, 2015)**

| County | Road Name | From | To | Segment Length | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Travis | IH 35 | US 290 N / SS69 | Ben White Blvd / SH71 | 7.93 | 975,552 |
| Harris | Southwest Fwy / US 59 | West Loop S/ IH 610 | South Fwy / SH 288 | 5.37 | 609,082 |
| Tarrant | North Fwy / IH 35W / US 287 | US 81 / US 287 | 28th St / SH 183 | 5.37 | 599,739 |
| Dallas | Lyndon B Johnson / IH 635 | Stemmons Fwy / IH 35 E / US 77 | US 75 | 8.01 | 578,542 |
| Harris | North Fwy / IH 45 | North Sam Houston Pkwy E / SL 8 | N Loop Fwy / IH 610 | 9.90 | 524,701 |
| Harris | Katy Fwy / IH10 / US 90 | W Loop N Fwy / IH610 | North Fwy / IH 45 | 5.08 | 519,820 |
| Dallas | US 75 | Lyndon B Johnson / IH 635 | Woodall Rodgers Freeway / SS 366 | 9.27 | 501,265 |
| Harris | Northwest Fwy / US 290 | W Sam Houston Pkwy N / SL 8 | N Loop W Fwy / IH 610 | 8.38 | 500,008 |
| Harris | N Loop W Fwy / IH 610 | North Fwy / IH 45 | Katy Fwy / IH10/ US90 | 6.58 | 499,335 |
| Harris | Gulf Fwy / IH 45 | IH10 / US 90 | S Loop E Fwy /IH 610 | 6.88 | 458,650 |
| Dallas | E R L Thornton Fwy / IH 30 / US 67 | Jefferson Viaduct | Buckner Blvd / SL 12 E | 8.40 | 441,769 |
| Harris | Gulf Fwy / IH 45 | South Sam Houston Pkwy E / SL 8 | Nasa Pkwy / FM 528 | 7.73 | 363,613 |
| Dallas | US 75 | President George Bush Turnpike Toll Rd / SH 190 | Lyndon B Johnson / IH 635 | 6.45 | 362,364 |
| Dallas | IH 35E/ US 77 / US 67 | Tom Landry Fwy / IH 30 | Marvin D Love Fwy / US 67 | 5.34 | 359,414 |
| Harris | Katy Fwy / IH 10 / US 90 | W Sam Houston Pkwy / SL 8 | W Loop N Fwy / IH610 | 6.39 | 339,314 |

| County | Road Name | From | To | Segment Length | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Travis | Mopac Expwy / SL1 | US 183 | S Capital of Texas Hwy / SL 360 | 10.52 | 299,867 |
| Harris | Katy Fwy / IH 10 / US 90 | Grand Pkwy / SH 99 | N Eldridge Pkwy | 9.51 | 298,440 |
| Harris | Southwest Fwy / IH 69 / US 59 | W Loop S Fwy / IH 610 | W Sam Houston Pkwy S / SL 8 | 7.79 | 288,002 |
| Dallas | Dallas North Tollway | President George Bush Turnpike Toll Rd | Lyndon B Johnson / IH 635 | 6.19 | 223,514 |
| Travis | IH 35 | Parmer Ln / FM 734 | US 290 N / SS69 | 6.44 | 222,199 |
| Harris | North Fwy / IH 45 | Spring Cypress Rd / FM 2920 | North Sam Houston Pkwy E / SL 8 | 8.55 | 210,600 |
| Harris | W Loop S Fwy / IH 610 | Southwest Fwy / US 59 / IH 69 | South Fwy / SH 288 | 7.97 | 208,419 |
| Tarrant | SH 360 | Tom Landry Fwy / IH 30 | IH 20 | 5.67 | 193,351 |
| Tarrant | Airport Fwy / SH 121 | SH 26 | Northeast Loop 820 / IH 820 | 12.18 | 191,577 |
| Harris | Gulf Fwy / IH 45 | S Loop E Fwy / IH 610 | South Sam Houston Pkwy E / SL 8 | 14.55 | 188,397 |
| Bexar | McDermott Fwy / IH 10 / US 87 | Charles West Anderson Loop / SL 1604 N | Connally Loop N / IH 410 | 7.08 | 186,555 |
| Dallas | Lyndon B Johnson / IH 635 | Garland Ave / SH 78 | US 80 | 5.70 | 178,930 |
| Tarrant | SH 360 | Airport Fwy / SH 183 | Tom Landry Fwy / IH 30 | 5.55 | 176,944 |
| Harris | Westheimer Rd / FM 1093 | W Sam Houston Pkwy S / SL 8 | West Loop S/ IH 610 | 6.48 | 175,985 |
| Bexar | Connally Loop NW / IH 410 | McDermott Fwy / IH 10 / US 87 | Culebra Rd | 6.29 | 163,773 |

| County | Road Name | From | To | Segment Length | Annual Delay per Mile (person-hours) |
|---|---|---|---|---|---|
| Harris | South Fwy / SH 288 | S Loop W Fwy / IH 610 | South Sam Houston Pkwy / SL 8 | 5.57 | 162,033 |
| Harris | W Sam Houston Pkwy / SL 8 | Katy Fwy / IH10/ US90 | Southwest Fwy / IH 69 / US 59 | 8.60 | 160,737 |
| Harris | North Sam Houston Pkwy / SL 8 | Tomball Pkwy / SH 249 | Hardy Toll Rd | 8.04 | 159,245 |
| Dallas | Lyndon B Johnson / IH 635 | US 75 | Garland Ave / SH 78 | 7.41 | 157,870 |
| Harris | Cypress Creek Pkwy / FM 1960 | Tomball Pkwy / SH 249 | North Fwy / IH 45 | 8.55 | 154,925 |
| Bexar | Connally Loop N / IH 410 | McAllister Fwy / US 281 | N PanAm Expy / IH 35 | 5.63 | 153,604 |
| Harris | W Sam Houston Pkwy N / SL 8 | W Little York Road | Katy Fwy / IH10 / US90 | 6.41 | 153,245 |
| Tarrant | IH 35 W | IH 30 | IH 20 | 5.50 | 147,143 |
| Dallas | Walton Walker Blvd / SL 12 W | W Northwest Hwy / SL 12 N | IH 30 | 7.46 | 140,596 |
| Tarrant | North East loop 820 / IH 820 | North Fwy / IH 35 W | Baker Blvd / SH 183 | 6.76 | 140,583 |
| Dallas | Tom Landry Fwy / IH 30 | S Walton Walker Blvd / SL 12 W | Jefferson Viaduct | 6.04 | 138,800 |
| Harris | S Loop E Fwy / IH 610 | South Fwy / SH 288 | Gulf Fwy / IH 45 | 6.01 | 131,885 |
| Harris | E Loop Fwy / IH 610 | East Fwy / IH 10 | Gulf Fwy / IH 45 | 6.03 | 131,234 |
| Travis | S Capital of Texas Hwy / SL 360 | RM 2244 | W Ben White Blvd / US 290 / SH 71 | 5.06 | 128,418 |
| Dallas | Airport Fwy / SH 183 | SH 161 | N Walton Walker Blvd / SL 12 W | 6.02 | 122,637 |
| Tarrant | Tom Landry Fwy / IH 30 | E Loop 820 / IH 820 | SH 360 | 8.78 | 120,301 |

| County | Road Name | From | To | Segment Length | Annual Delay per Mile (person-hours) |
| --- | --- | --- | --- | --- | --- |
| Bexar | Charles West Anderson Loop / SL 1604 N | US 281 | McDermott Fwy / IH 10 / US 87 | 8.17 | 115,845 |
| Bexar | McAllister Fwy / US 281 | Connally Loop N / IH 410 | PanAm Expy / IH 35 | 6.35 | 115,128 |
| Harris | Southwest Fwy / US 59 | W Sam Houston Pkwy S / SL 8 | SH 6 | 5.35 | 114,702 |
| Tarrant | IH 35 W | Alliance Gateway / SH 170 | US 81 / US 287 | 5.08 | 110,809 |
| Bexar | Charles West Anderson Loop / SL 1604 NW | McDermott Fwy / IH 10 / US 87 | Braun Rd | 5.22 | 109,862 |
| Harris | Northwest Fwy / US 290 / SH 6 | Spring Cypress Rd | SH6 | 5.73 | 106,019 |
| Travis | US 183 | IH35 | E Ben White Blvd / SH 71 | 10.17 | 102,484 |

**Table A-4: Suggested Roadways for Preliminary CAV Truck Platooning Testing (Source: TTI, 2015)**

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) | Annual Truck Delay per Mile (person-hours) |
|---|---|---|---|---|---|---|
| Harris | North Fwy / IH 45 | Spring Cypress Rd / FM 2920 | North Sam Houston Pkwy E / SL 8 | 8.55 | 210,600 | 19,324 |
| Harris | Katy Fwy / IH10 / US 90 | W Sam Houston Pkwy / SL 8 | W Loop N Fwy / IH 610 | 6.39 | 339,314 | 19,227 |
| Harris | Gulf Fwy / IH 45 | S Loop E Fwy / IH 610 | South Sam Houston Pkwy E / SL 8 | 14.55 | 188,397 | 17,927 |
| Tarrant | IH 35 W | Alliance Gateway / SH 170 | US 81 / US 287 | 5.08 | 110,809 | 16,545 |
| Hidalgo | IH 69C / US 281 | E Canton Rd | IH 2 / US 83 | 5.72 | 41,503 | 16,146 |
| Williamson | Palm Valley Blvd / US 79 | N IH 35 | FM 685 | 7.84 | 37,408 | 16,019 |
| Denton | IH 35 E / US 77 | Lillian Miller Pkwy / SL 288 | N Denton Dr | 5.59 | 185,689 | 15,370 |
| Harris | Northwest Fwy / US 290 / SH 6 | Spring Cypress Rd | SH 6 | 5.73 | 106,019 | 15,007 |
| Dallas | Tom Landry Fwy / IH 30 | S Walton Walker Blvd / SL 12 W | Jefferson Viaduct | 6.04 | 138,800 | 13,974 |
| Tarrant | Airport Fwy / SH 121 | SH 26 | Northeast Loop 820 / IH 820 | 12.18 | 191,577 | 13,713 |
| Harris | Westheimer Rd / FM 1093 | W Sam Houston Pkwy S / SL 8 | West Loop S / IH 610 | 6.48 | 175,985 | 13,494 |
| Harris | South Fwy / SH 288 | S Loop W Fwy / IH 610 | South Sam Houston Pkwy / SL 8 | 5.57 | 162,033 | 13,370 |
| Brazos | S TX Ave / BS 6R | E Villa Maria | Earl Rudder / SH 6 (Deacon Dr) | 5.26 | 69,431 | 13,266 |
| Denton | FM 1171 | Flower Mound Rd | BS 121H | 8.18 | 50,004 | 13,200 |
| Tarrant | North East Loop 820 / IH 820 | North Fwy / IH 35 W | Baker Blvd / SH 183 | 6.76 | 140,583 | 12,906 |
| Tarrant | IH 35 W | IH 30 | IH 20 | 5.50 | 147,143 | 12,712 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) | Annual Truck Delay per Mile (person-hours) |
|---|---|---|---|---|---|---|
| Collin | Sam Johnson Hwy / US 75 | Sam Rayburn Tollway / SH 121 / SH 399 | President George Bush Turnpike Toll Rd / SH 190 | 11.51 | 173,879 | 12,654 |
| Harris | W Loop S Fwy / IH 610 | Southwest Fwy / US 59 / IH 69 | South Fwy / SH 288 | 7.97 | 208,419 | 12,592 |
| Tarrant | IH 30 / US 377 | Camp Bowie Blvd / US 377 | IH 35 W | 5.08 | 97,136 | 12,272 |
| Williamson | IH 35 | SH 45 / Louis Henna Blvd | Parmer Ln / FM 734 | 5.55 | 104,216 | 12,199 |
| Harris | Tomball Pkwy / SH 249 | North Sam Houston Pkwy W / SL 8 | North Fwy / IH 45 | 6.92 | 78,577 | 12,090 |
| Smith | Southwest Loop 323 | Dallas Hwy / W Ervin St / SH 64 | S Broadway Ave / US 69 | 5.35 | 46,968 | 12,034 |
| Denton | Justin Rd / FM 407 | McMakin Rd | IH 35E / US 77 | 6.82 | 38,369 | 11,394 |
| Bexar | Charles West Anderson Loop / SL 1604 N | US 281 | McDermott Fwy / IH 10 / US 87 | 8.17 | 115,845 | 11,335 |
| Bexar | Charles West Anderson Loop / SL 1604 NW | McDermott Fwy / IH 10 / US 87 | Braun Rd | 5.22 | 109,862 | 11,071 |
| Dallas | Preston Rd / SH 289 | Sam Rayburn Tollway / SH 121 | IH 635 | 12.12 | 73,043 | 11,032 |
| Tarrant | SH 360 | Tom Landry Fwy / IH 30 | IH 20 | 5.67 | 193,351 | 10,714 |
| Fort Bend | FM 762 | Jackson St / UA 90 | Crabb River Rd / FM 2759 | 5.26 | 42,153 | 10,231 |
| Harris | East Fwy / IH 10 | E Sam Houston Pkwy / SL 8 | SS 330 | 5.76 | 55,191 | 10,075 |

**Table A-5: Suggested Roadways for Intermediate CAV Truck Platooning Testing (Source: TTI, 2015)**

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) | Annual Truck Delay per Mile (person-hours) |
|---|---|---|---|---|---|---|
| Harris | Gulf Fwy / IH 45 | IH10 / US 90 | S Loop E Fwy / IH 610 | 6.88 | 458,650 | 46,138 |
| Harris | Northwest Fwy / US 290 | W Sam Houston Pkwy N / SL 8 | N Loop W Fwy / IH 610 | 8.38 | 500,008 | 42,465 |
| Dallas | E R L Thornton Fwy / IH 30 / US 67 | Jefferson Viaduct | Buckner Blvd / SL 12 E | 8.40 | 441,769 | 40,667 |
| Harris | N Loop W Fwy / IH 610 | North Fwy / IH 45 | Katy Fwy / IH10 / US 90 | 6.58 | 499,335 | 39,731 |
| Dallas | US 75 | Lyndon B Johnson / IH 635 | Woodall Rodgers Freeway / SS 366 | 9.27 | 501,265 | 39,318 |
| Harris | Katy Fwy / IH10 / US 90 | W Loop N Fwy / IH 610 | North Fwy / IH 45 | 5.08 | 519,820 | 33,636 |
| Harris | Gulf Fwy / IH 45 | South Sam Houston Pkwy E / SL 8 | Nasa Pkwy / FM 528 | 7.73 | 363,613 | 32,217 |
| Dallas | IH 35E / US 77 / US 67 | Tom Landry Fwy / IH 30 | Marvin D Love Fwy / US 67 | 5.34 | 359,414 | 31,709 |
| Denton | IH 35 E / US 77 | BS 121 H | Lyndon B Johnson / IH 635 | 10.28 | 325,116 | 28,255 |
| Williamson | IH 35 | RM 1431 | SH 45 / Louis Henna Blvd | 5.07 | 167,436 | 27,294 |
| Dallas | US 75 | President George Bush Turnpike Toll Rd / SH 190 | Lyndon B Johnson / IH 635 | 6.45 | 362,364 | 27,173 |
| Travis | IH 35 | Parmer Ln / FM 734 | US 290 N / SS69 | 6.44 | 222,199 | 26,191 |
| Harris | Katy Fwy / IH10 / US9 0 | Grand Pkwy / SH 99 | N Eldridge Pkwy | 9.51 | 298,440 | 26,148 |
| Dallas | Lyndon B Johnson / IH 635 | Garland Ave / SH 78 | US 80 | 5.70 | 178,930 | 24,659 |
| Harris | Southwest Fwy / IH 69 / US 59 | W Loop S Fwy / IH 610 | W Sam Houston Pkwy S / SL 8 | 7.79 | 288,002 | 24,125 |

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) | Annual Truck Delay per Mile (person-hours) |
|---|---|---|---|---|---|---|
| Montgomery | North Fwy / IH 45 | Lake Front Cir | Spring Cypress Rd / FM 2920 | 6.89 | 254,925 | 22,091 |
| Dallas | Lyndon B Johnson / IH 635 | US 75 | Garland Ave / SH 78 | 7.41 | 157,870 | 20,823 |

**Table A-6: Suggested Roadways for Advanced CAV Truck Platooning Testing (Source: TTI, 2015)**

| County | Road Name | From | To | Segment Length (miles) | Annual Delay per Mile (person-hours) | Annual Truck Delay per Mile (person-hours) |
|---|---|---|---|---|---|---|
| Travis | IH 35 | US 290 N / SS69 | Ben White Blvd / SH71 | 7.93 | 975,552 | 114,930 |
| Dallas | Lyndon B Johnson / IH 635 | Stemmons Fwy / IH 35 E / US 77 | US 75 | 8.01 | 578,542 | 83,394 |
| Tarrant | North Fwy / IH 35W / US 287 | US 81 / US 287 | 28th St / SH 183 | 5.37 | 599,739 | 82,273 |
| Harris | Southwest Fwy / US 59 | West Loop S / IH 610 | South Fwy / SH 288 | 5.37 | 609,082 | 52,955 |
| Harris | North Fwy / IH 45 | North Sam Houston Pkwy E / SL 8 | N Loop Fwy / IH 610 | 9.90 | 524,701 | 50,923 |