Benefits Estimation Model for Automated Vehicle Operations

Phase 2 Final Report

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16. Abstract

Automated vehicles have the potential to bring about transformative safety, mobility, energy, and environmental benefits to the surface transportation system. They are also being introduced into a complex transportation system, where second-order impacts, such as the possibility of increased vehicle-miles traveled, are of significant concern. Given the complexity of the impacts, a modeling framework is needed to ensure that they are adequately captured. This report updates the Framework from our August 2015 report and our June 2016 interim report, and summarizes the safety, mobility, energy/emissions, and travel behavior (user response) modeling that has been performed during FY 2017.

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Table of Contents

List of Figures

List of Tables

Executive Summary

This report summarizes the activities conducted during the Automated Vehicle (AV) Benefits Estimation Project between 2016 and 2017. This project is an expansion of earlier work and the resulting document provides summaries as well as updates based on the most recent information. Elements of the Benefits Framework include:

- Travel Behavior (was called Transportation System Usage in the 2015 report)
- Safety
- Vehicle Operations (was called Vehicle Mobility in the 2015 report)
- Energy / Emissions
- Socio-Economic Impacts (was called Economic Analysis in the 2015 report)
- Personal Mobility (was called Accessibility in the 2015 report)
- Network Efficiency (was called Regional Mobility in the 2015 report)
- Public Health (new since the 2015 report)
- Land Use

During the past year, efforts focused on the modeling of travel behavior, safety, vehicle operations, and energy/emissions, along with initial work on socio-economic impacts (economy and jobs). Continuing efforts focus on international collaboration in order to facilitate the use of findings and data from projects around the world. Below are brief descriptions of each chapter within this document.

Travel Behavior focuses on two elements of the travel demand modeling chain: vehicle ownership modeling and mode choice modeling. Initial work in this impact area included using ideas from system dynamics modeling to elucidate key factors in user response to AVs, especially as they relate to the decision to purchase a privately-owned vehicle (POV) or rely on shared, automated vehicles. Recent efforts, expanding on this initial work, identified impact linkages for these decisions, and will be used to develop a proof-of-concept model, using “typical” parameters from travel demand models.

Safety details the significant challenge to establish a baseline for modeling. In 2015, preliminary target crash populations that could be affected by automation were identified. Building off of this initial effort, this document highlights the use of available naturalistic driving data sets to establish a baseline of driving conflicts and historical crash data sets to determine baseline crashes that may be encountered by automated vehicles. This baseline condition sets a foundation for estimating system effectiveness, as this baseline condition will be compared to the applicable treatment condition (i.e., conflicts and crashes with automation), when available.

Vehicle Operations explores the creation of a model of an idealized freeway in PTV Vissim, a traffic microsimulation product. Vissim car-following parameters were adjusted to mimic an AV operation by removing the human “unconscious oscillations” in car following. The simulation resulted in a small (5%) improvement in link capacity, an expected result as there was no change in desired following distance. Ongoing efforts include the testing of the Intelligent Driver Model (IDM) and the Microscopic Model for Simulation of Intelligent Cruise Control (MIXIC) in order to model more complex scenarios.

Energy / Emissions focuses on a script developed to create an operating mode distribution from Vissim output. This distribution was then provided to the EPA MOVES2014a model, to provide fuel consumption and tailpipe emission results.

Finally, in Economy and Jobs, we introduce the larger economic impacts of AV adoption.

Chapter 1 Benefits Framework

Automated vehicles (AVs) have the potential to bring about transformative safety, mobility, energy, and environmental benefits to the surface transportation system. These benefits may include crash avoidance; reduced energy consumption and vehicle emissions; reduced travel times; improved travel time reliability and multi-modal connections; improved transportation system efficiency; and improved personal mobility, particularly for those who do not have access to driving a motor vehicle.

AVs are being introduced into a complex transportation system. Second order impacts, such as the possibility of increased vehicle-miles travelled (VMT), are of significant concern. Given the complexity of the impacts, a modeling framework is needed to ensure that they are adequately captured. The Framework is envisioned to increase the ability to adequately portray the potential and actual impacts of automated vehicle technologies and benefits to the Nation's transportation system.

The initial Framework was developed in Phase 1 of this project conducted during 2014-2015; an updated version is presented in this chapter. In 2015, the Impact Assessment subgroup of the European Union-United States-Japan Automation in Road Transportation Working group was established to further international collaboration in this work. The updates in this chapter draw from both the work of the Impact Assessment subgroup and our recent work in system dynamics. It is organized as follows:

- Audience for the Framework
- Classification of AV systems
- Framework, Direct and Indirect impacts
- Sources of Uncertainty
- Impact Mechanisms
- Approaches inspired by system dynamics to characterize potential impacts

1.1 Audience for the Framework

There are two primary audiences for this report: designers of field operational tests (FOTs) and policy-makers.

FOT designers may find the Framework useful during the early in the systems engineering process (concept exploration[1], concept-of-operations[2] development, defining the aims objectives, research questions, and hypotheses[3]). The Framework facilitates starting with the end in mind[4]. For FOT designers, the Framework provides a structure for addressing the "Where", "What" and "Why" of the project. Section 1.2 of this document describes the elements of AV system classification, which is necessary for such a Framework, including, but not limited to, the operational design domain (the Where and What). Later, the elements of the Framework itself (section 1.3) help describe "Why" the project is being done. The associated Key Performance Indicators (KPIs) provide initial thoughts on measures for validation, to define the data that should be collected, and to

[1] Section 4.2.1 of ITS Systems Engineering Guide (National ITS Architecture Team, 2007)
[2] Section 4.3 of ITS Systems Engineering Guide (National ITS Architecture Team, 2007)
[3] Activity 2 in the FESTA framework (Barnard et al., 2017)
[4] See "Start with Your Eye on the Finish Line" in Section 3.2.2 of ITS Systems Engineering Guide (National ITS Architecture Team, 2007)

ensure that the information gathered maximizes the value of the test. Those performing impact assessment for the automation of surface transportation can use it as a starting point in design of evaluation work.

Policy-makers may use the Framework to support policy analysis, long-range scenario-based planning, and major infrastructure investment decisions, where various automation futures are being investigated. For policy-makers, the direct and indirect impact areas, as well as their associated linkages, provide a path from the results of a field test, towards potential larger societal impacts. As automation is deployed, the Framework may be applied to evaluate the new data that becomes available, and can provide insight as to what related data should be collected.

Finally, for both FOT designers and policy-makers, the Framework can support exploratory analysis. For example, users can take broad assumptions about either inputs or outcomes in the future and trace them back through the Framework to other things that should be considered or measured. A specific example of the latter might be to consider different roles of shared mobility in relation to transit (e.g., ranging from effective last-mile service to full replacement) and mapping that back out to total trips, new types of bottlenecks (e.g., at pickup/drop-off points), and other aspects of demand formation.

1.2 AV System Classification

The operational design domain (ODD) is important to the characterization of automated vehicle systems. In the European FESTA Framework, these elements are described as situational variables. These characteristics detail answers to questions such as: What is needed (road markings, signs, signals, mapping, V2X communications, winter maintenance) to support automated driving? More broadly, what is the operational design domain for the automation application? According to SAE J3016 (SAE, 2016), the operational design domain may include geographic, roadway, environmental, traffic, speed, and/or temporal limitations. It may also include one or more driving modes. Examples of driving modes include expressway merging, high-speed cruising, and low-speed traffic jam.

Infrastructure requirements can be characterized by a detailed description of the operational design domain, to indicate where the automation application is designed to function, and where it has been tested. Infrastructure elements of the operational design domain include:

- Specific location where the automation system may operate
- Level of mapping needed where the automated system operates
- Type of road: number of lanes and carriageways, required markings, pavement type
- Types of intersections: merge, diverge, roundabout, traffic signal, stop/yield sign
- Usage of road: exclusive to AVs, shared with other motor vehicles, shared with bicyclists and pedestrians
- Design speed
- Daytime / nighttime
- Types of road surface conditions: dry, wet, snowy, icy
- Visibility: clear, rain, snow, fog
- Temperature, atmospheric pressure

It is important to specify the description of the system and the service for which impact assessment is made, and thus providing the implementation of vehicle automation should be the first step. Otherwise, researchers risk comparing very different services even though they have a similar ODDs. The FESTA Handbook (Barnard et al., 2017) addresses this classification through specifying use cases. The description of the automation system or service should include (at least):

- Purpose of the system. Is it for person travel, or freight? Within person-travel, is it aimed at area residents, visitors, specifically at persons with disabilities, etc.? For freight, consider the type and size of shipments.
- Service type. Is it for short (a few km) or long haul? Does the system serve individuals or groups? Is it on a fixed route, or may the route vary? Is it a specialized system with a limited ODD (e.g., valet parking)?
- Vehicle ownership, management, and maintenance. Does the system envision single privately-owned vehicles (similar to most automobiles today) or vehicles that are part of a larger fleet?
- Vehicle type(s) (e.g., passenger vehicle, mini bus, large bus, truck, etc.)
- SAE level of automation
- Available automated driving functions. What vehicle control is automated? How is the driving environment being monitored? Is there dynamic routing? Are there communications (V2X) with other road users or infrastructure?

1.3 Direct and Indirect Impacts of Automation

This section describes a framework for assessing the impacts of AV applications. It then explains each type of impact area in further detail, including providing a list of proposed key performance indicators (KPIs) as a way to monitor changes in the overall system. It is important to note the various terminology presented in this section. An impact is defined as an action caused by automated vehicles that has an effect on other actions. An impact area is defined as categories of similar impact types or actions, such as safety, vehicle operations, and personal mobility among others.

AV impacts may be divided into two major groups: direct and indirect. Figure 1 depicts the impact areas and their respective linkages. Direct impacts are those which have a relatively clear cause-effect relationship with the primary activity or action. They are generally easier to capture, measure and assess, and are often (though not always) immediate to short-term in nature. In Figure 1, they are in the upper left, and include safety, vehicle operations, energy/emissions, and personal mobility. The others are indirect impacts. Indirect impacts can be characterized as secondary, tertiary, or still further removed from the original direct impact. Indirect impacts summarize the broader effects of the individual direct impacts and are produced as the result of a path/chain of impacts, often with complex interactions and external factors. They are typically more difficult to measure and are longer than the time horizon of a field test.[5]

The following Framework was presented in several public forums since inception, including: the 2015, 2016, and 2017 Automated Vehicles Symposiums; the 2016 Transportation Research Board Annual Meeting; the 2016 SAE Government-Industry Meeting; the 2016 FOT-Net Data Workshop in Leeds, United Kingdom; the November 2016 SIP-adus meeting in Tokyo, Japan; and the April 2017 Connected and Automated Driving Conference in Brussels, Germany. Based on feedback received at these and other venues, a new impact area, Public Health, was added, and several other impact areas were renamed.

[5] This explanation is inspired by that of direct and indirect environmental impacts of road development in (World Bank, 1997)

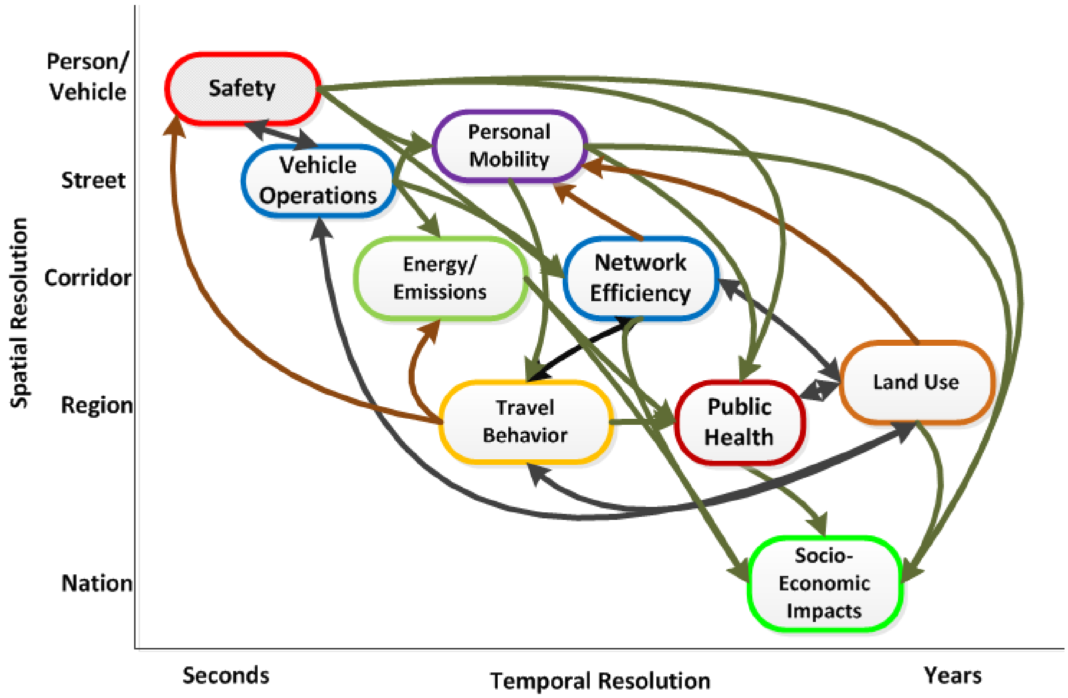

Figure 1: Automated Vehicle Benefits Framework

In Figure 1, forward links are represented in green arrows, these impacts are those in which short term changes in an impact area affect longer term changes in another impact area. For example, a change in personal mobility, such as an increase or decrease in shorter walking trips will overtime affect the longer term impacts of public health. Feedback links are represented, below, in brown, these impacts are those in which more holistic or wider reaching changes in impacts affect shorter term and more localized changes in other impact areas. For example, a change in land use and zoning policy will affect the options available for travelers to make personal mobility choices. Finally, those links going in both directions are in black and denote a mutual impact relationship.

1.3.1 Direct Impacts

Direct Impacts are those that can be measured in a Field Operational Test (FOT). They then can be scaled up to a regional or national level, and can lead to indirect impacts. For example, a FOT can measure driving conflicts (Safety); driver/traveler behavior, car following, and intersection performance (Vehicle Operations); energy consumption and tailpipe emissions (Energy / Emissions); and the comfort of the user or the user's ability to multi-task while in the vehicle (Personal Mobility). FOTs can also provide insights into the infrastructure requirements of an automation application. In this section, we describe the impact areas, and propose key performance indicators (KPIs) for measuring the impacts.

The below impact areas are examples of what should be considered in the design of a FOT. Note that specialized use cases, such as truck platooning, may require a unique set of measures not applicable to other FOTs (e.g., number of platoons formed, what share of the vehicle km/miles was driven as part of a platoon).

Response of drivers and other road users: The response of users to the system is not a benefit or dis-benefit by itself (and is therefore not included in Figure 1), but it is an important impact area that will affect both the direct and indirect benefits. How do the vehicle occupants or other road users respond to the automation application? For driver assistance systems, one question is whether the drivers use the system, on which kind of journeys or environments and in which kind of circumstances, and if relevant, what parameters they choose (e.g., car following distance). The driver's degree of engagement with the driving task is also relevant (e.g., is the driver treating a Level 2 system as though it is a Level 4 system?). For applications operating in mixed traffic environments, the behavior of other road users (e.g., drivers, pedestrians, bicyclists) is also relevant. KPIs will depend on the application being deployed, and may include:

- Driver / vehicle occupant characteristics (age, gender, driving license status)
- Whether the driver uses the automated driving (AD) system
- Degree of engagement with the driving task
- In-car activity (secondary tasks when driving, primary activities when not driving)
- Conflicts created by the driver
- Conflicts created by other road users (e.g., pedestrian stepping in front of an AV)

Vehicle Operations: Vehicle operations include acceleration, deceleration, lane keeping, car following, lane changing, and gap acceptance which all affect road (network) capacity. Relevant automation applications encompass those which provide longitudinal and/or lateral control with respect to the road and other vehicles. KPIs include:

- Speed variation during constant speed travel (relevant to car-following)
- Lateral position variation (relevant to lane-keeping and to aerodynamics for platooning)
- Use of indicator signal
- Normal longitudinal acceleration and deceleration
- Lateral acceleration (around curves)
- Emergency deceleration
- Jerk (rate of change in acceleration; relevant to passenger comfort)
- Car following performance (distance, time-headway, variation)
- Gap-acceptance at intersections or in lane changes
- Transfer of control between operator and vehicle (turning system on/off, manual overrule)

Safety: Safety is measured as fatalities, injuries, and property damage for vehicle occupants and other road users. Other road users may include pedestrians, bicyclists, slow-moving vehicles, construction workers, and first responders. Nearly all AV applications, ranging from SAE Level 1 collision avoidance systems to SAE Level 5 self-driving vehicles, have potential safety impacts. A challenge with developing safety assessments for AVs is that actual crashes are rare events; therefore, proxy measures are often used. These measures may include selected traffic violations, instances where a human driver must take control of the vehicle, exposure to near-crash situations, and responses to near-crash situations. KPIs will be normalized to vehicle-km driven or vehicle-hours driven, and include:

- Number and severity of crashes by type (property damage, injury, and fatality), change in number of crashes (%)
- Number of conflicts encountered where time-to-collision (TTC) is less than a pre-determined threshold
- TTC at brake onset
- Minimum TTC (shortest TTC observed during a braking event)
- Instances with hard braking (high deceleration)
- Number of instances where the driver must take manual control
- False positives – instances where the vehicle takes unnecessary collision avoidance action

- False negatives – instances where the vehicle fails to take necessary action. These may be significant, especially in unfavorable operating conditions such as those involving reduced visibility.
- Selected traffic violations[6]

Energy / Environment: The energy and emissions category includes both the energy consumption of the vehicle through a driving cycle, and tailpipe emissions of pollutants including greenhouse gases. The direct energy/emissions impacts come from the change in the driving cycle. Changes in vehicle propulsion (e.g., electric vehicles) may also have a significant effect on tailpipe emissions. KPIs include:

- Vehicle energy consumption (kWh, litres / 100 km, gallons/mile or electric equivalent)
- Personal energy consumption (kWh / person-mile and kWh/ person)
- Total fossil energy (gasoline, diesel, CNG, LNG) consumption from highway transportation
- Noise levels along roads (in dB)
- Tailpipe[7] carbon dioxide (CO_2) emissions
    - Total
    - Per person
    - Per vehicle-mile
- Tailpipe criteria pollutant[8] emissions
    - Total
    - Per person
    - Per vehicle-mile

Personal Mobility: Mobility from the perspective of a user includes journey quality (comfort, use potential of in-vehicle time), travel time, cost, and whether the travel option is available (e.g., a non-motorist). This impact area also includes equity and accessibility considerations. The higher levels of automation will have the most significant impacts, by providing mobility for non-motorists and enabling travelers to engage in activities other than the driving task. These encompass first mile / last mile services and accessibility applications. Challenges in measuring personal mobility impacts include the variety of sub-populations who may be affected in different ways, and the difficulty in assessing the actual value of automation to a person based on survey data. To address these challenges, travel time indicators can be evaluated at the network level – rather than the individual level. Network efficiency is addressed in Section 1.3.2 below. KPIs for this impact area may be measured as user friendliness and acceptance of systems, as well as:

- Total time spent travelling (e.g., per day)
- User perception of travel time changes
- Type and duration of activities when not operating the vehicle (e.g., in higher levels of automation)
- Percent of time or population for which a travel option is available
- User perceptions of quality, reliability, and comfort expressed (i.e., on a Likert scale)

[6] Some violations may have little significance, e.g., traveling at 95 kph (59 mph) in a 90 kph (56 mph) zone, while others are of greater significance, e.g., passing through a red signal several seconds after it has turned red.
[7] In assessing automation benefits, it may be necessary to assume that types of fuel used by automated and non-automated vehicles are the same, at least in the near-term. It may be beyond the scope of an FOT to assess the CO_2 emissions from electricity generation.
[8] U.S. criteria pollutants include ozone, particulate matter, carbon monoxide, nitrogen oxides, sulfur dioxide, and lead. See http://www.epa.gov/airquality/urbanair/

Cost: The production cost of an AV application is important for assessing the future business case for deployment and ultimate usage. Key performance indicators (KPIs) include:

- Estimate of capital cost per vehicle for the deployed system
- Estimate of cost of purchased AV (market price)
- Estimate of operating cost for the deployed system (per vehicle-hour or per vehicle-km)
- Estimate of changes in infrastructure costs (passed on via taxes)

1.3.2 Indirect Impacts

In assessing indirect impacts, note that fleet composition and service offerings might change. For example:

- Better crash avoidance may enable the use of lighter-weight vehicles (e.g., material and energy use or emissions) and prevent crash-related congestion (e.g., network efficiency)
- The advanced control systems used for automation may also contribute to electrification (e.g., energy use and emissions)
- If there is no human driver, the layout of the vehicle might change (e.g., energy use)
- Without the labor cost of a human driver, it may become economical to use smaller vehicles for both trucking and transit (e.g., energy use and network efficiency).

Other indirect impacts that may be of concern are the impacts on different stakeholders of the transportation industry, such as non-motorists and professional drivers.

Network Efficiency: Network efficiency refers to lane, link, and intersection capacity and throughput in a regional transport network. It also refers to travel time and travel time reliability. Improved safety may improve network efficiency via reduced incident delay. Changes in vehicle operations (e.g., car following) will also affect network efficiency via changes in car following distance, merge behavior and gap acceptance. Changes in transport modes or mileage driven by AVs will also affect network efficiency. KPIs include the following, depending on the level of detail desired:

- At the road segment level:
    - Capacity at design speed
    - Maximum capacity
    - Free flow speed
    - Median speed
    - 5^{th} percentile speed - addresses “worst case” reliability
- For an intersection approach
    - Vehicles per hour through a particular intersection approach (throughput), normalized to number of lanes and proportion of green time.
- For a corridor
    - Average travel time (minutes)
    - 95^{th} percentile travel time (minutes). This measure addresses travel time reliability.
- For a region
    - Total number of vehicle trips (used for normalization)
    - Total travel distance (used for normalization)
    - Total travel time
    - Average trip duration
    - Average trip length

- o Average travel speed
- o Total travel delay

Travel Behavior: A traveler may respond to AV options, including new service offerings, by changing travel behavior. There may be more or fewer trips. Modes, routes, and destinations may change. Higher level automation applications that have a significant effect on personal mobility or labor could have a significant effect on travel behavior. KPIs include:

- Number and type of person and vehicle trips
- Share of transport modes (modal split)
- Share of road types used
- Total person and vehicle miles/kms travelled
- Network-level travel time savings

Asset Management: Automation may affect infrastructure assets required in several ways, though significant uncertainty still remains in this area. Because of this uncertainty, identifying specific indicators is difficult, but the following examples suggest some areas in which infrastructure assets may be affected:

- Number of lanes and lane widths
- Use of hard shoulder (for hard-shoulder running or as emergency stop area for mal-functioning AVs)
- V2I infrastructure used by automation
- Size and weight implications of changed fleet composition
- Spacing of heavy vehicles, which may affect bridge deterioration
- Effect of travel behavior changes on trip making. If travelers respond to automation by making more trips, more road capacity may be needed. On the other hand, if automation leads to greater use of shared, rather than owned, vehicles, the infrastructure required for parking may be reduced. Changes in trip making may affect the assets required.

Public Health: Automation may impact the health (physical and mental) of individuals and entire communities via safety, air pollution, amount of walking and bicycling, as well as access to medical care, food, employment, education, and recreation. KPIs include:

- Concentrations of air pollutants as listed above under direct impacts)
- Quality-adjusted life years
- Modal share and total mileage travelled (kms) by active modes of transportation
- Perception of safety and comfort of vulnerable road users

Land Use: Automation may affect the use of land for transport functions (e.g., parking, road geometry). Longer term land use changes may include community planning i.e. location and density of housing, road network design, employment, and recreation. The number of factors that contribute to long-term land use changes makes distinguishing the changes contributed by automation a particular challenge. Additional research in this area would be required to establish meaningful KPIs.

Socio-Economic Impacts: Improved safety, use of time, freight movement, travel options (for motorists and non-motorists), public health, land use, and effects of changed emissions (including climate change) will have longer-term economic impacts. Automation may also have substantial impacts on labor markets and industries. More research is needed; however, preliminary KPIs include the following:

- Gross Domestic Product: total, per capita, and per hour worked
- Total factor productivity and multifactor productivity estimates

- Work time lost from traffic crashes (hours per year, overall and per capita; monetary value)
- Work time lost from illnesses related to air pollution
- Work time gained due to ability to multitask while traveling
- Labor force participation rate – overall and for non-drivers.
- Job losses for professional drivers

1.4 Sources of Uncertainty for AV Impacts

The sources of uncertainty surrounding AVs can be classified in several ways. (Jette, Perlman, & Santalucia, 2017) group the key factors affecting deployment into supply-side, demand-side and governance. Following the example of (Srinivasan, Smith, & Milakis, 2016), this report focuses on subsets of these: technology, policy, and user attitudes and behavior (abbreviated in this document as user response). Some of the specific factors below are adapted from (Srinivasan et al., 2016).

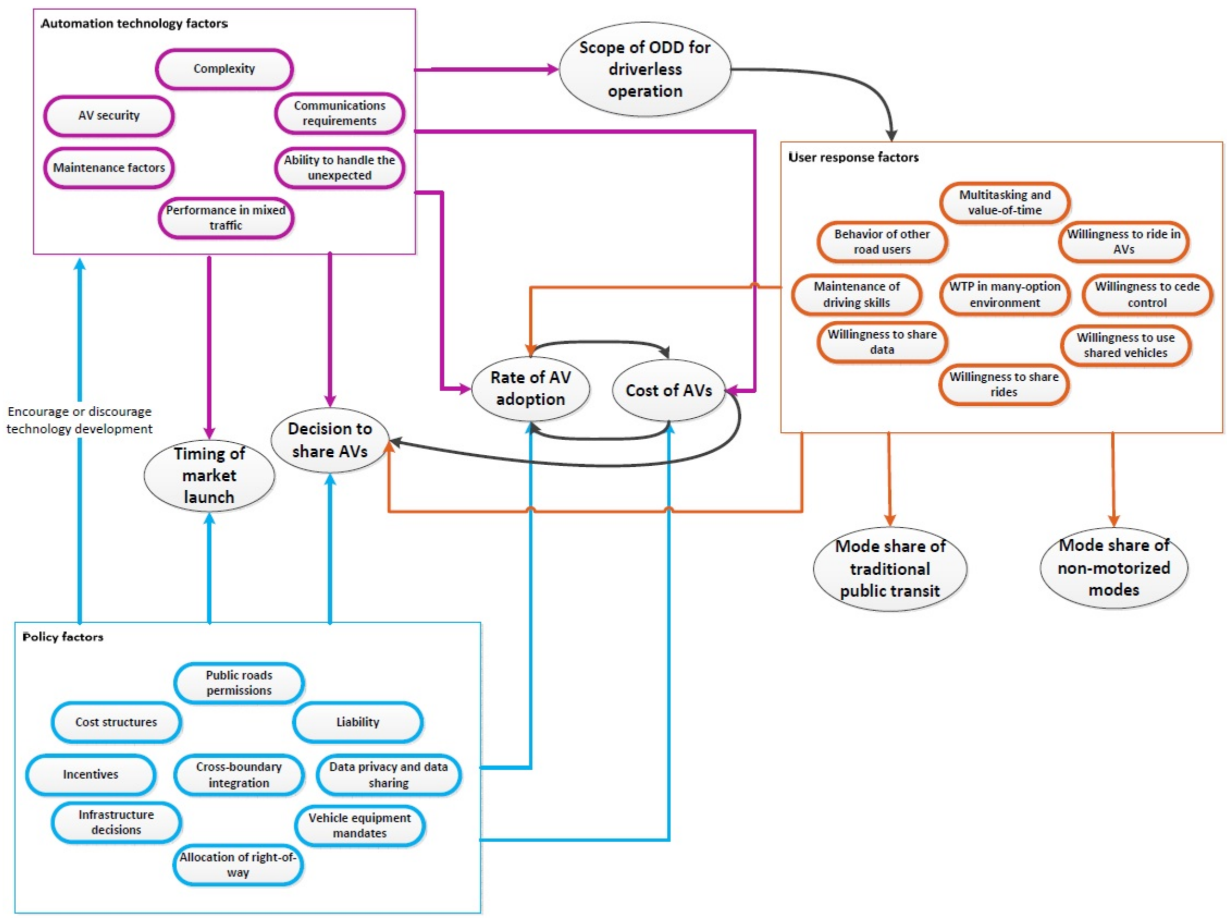

Figure 2: Uncertainties of AVs

Technological factors include those that affect the ODD, and factors that affect cost. Factors that affect the ODD include:

- Sensor and control system performance
- The degree to which ad hoc communications (e.g., Wi-Fi, DSRC, 4G, 5G) will be required for successful deployment
- The degree to which vehicle sensor, processing and control systems will be able to handle unexpected situations
- Performance of the vehicles in mixed traffic, and effect on safety and road capacity

Factors that affect cost include:

- Capability and ease of vehicle systems maintenance over time
- Functionality to ensure AV hardware and software security
- The complexity of design and manufacturing of sensors, processing and control

The outcomes of the technology factors will impact the extent of the ODD for Level 4 vehicles, but will also influence the cost of the vehicles, as well as the relative desirability of shared versus privately owned vehicles (due to maintenance needs, and possible rapid obsolescence of the sensors and control systems).

Policy factors include legislation/legal structure, risk assessment, the cost structure and the physical space provided for AVs.

Legislative and legal elements include:

- Permission to test on public roads
- Permission to operate on public roads
- Liability regimes
- Data privacy policies
- Interoperability: the extent to which AV systems are integrated to permit smooth travel across jurisdictional boundaries
- Requirements to share data on testing among vehicle manufacturers and operators
- Vehicle equipment requirements. There may be additional requirements for heavy vehicles operating in platoons.

Risk assessment elements include:

- Data protection rules
- Security requirements

Cost structure elements include:

- Incentives for (or against) adoption of automated vehicles; shared vehicles
- User cost structures for vehicle ownership and use (purchase, insurance, registration, fuel, etc.)

Finally, elements of physical space include:

- Allocation of public right-of-way for legacy vehicles, automated vehicles, transit, bicycling, walking and parking
- Infrastructure decisions to accommodate automation and other modes

The outcomes of these policy factors will affect how and to what extent AVs are adopted and used. They will also affect technological development and the timing of market launch because they affect the business model; if policies increase or decrease demand, there will be more or less incentive for OEMs, electronics developers and systems integrators to focus on AV technology.

User response factors include:

Value and tradeoffs elements include:

- Attractiveness of multitasking (i.e., being able to do something other than keep one's attention on the road)
- Value-of-travel-time in the multitasking environment
- Willingness to share data on travel patterns (to enable delivery of shared vehicle services)
- Willingness to pay (WTP) for marginal level of service improvements when there are more services at more price points than are available today (e.g., shared vehicles available to more people; different sizes of shared vehicle; shared ride vs. private ride in shared vehicle; conventional fixed-route public transit; non-motorized modes; etc.) (following (Chase, 2014))

Desire to drive elements include:

- Willingness of users to ride in automated vehicles (e.g., factors related to discomfort around there being no human driver)
- Willingness to 'cede control' (Srinivasan et al., 2016) in driving or routing (e.g., factors relating to enjoying the process of driving)
- Maintenance of driving skills where Level 4 automation is available in some places

Mixed environment elements include:

- Behavior of other road users (non-AVs; non-motorized) in the presence of automated vehicles
- Interactions with vulnerable road users

Vehicle ownership and use pattern elements include:

- Willingness to use shared vehicles rather than owned vehicles
- Willingness to share rides with other users

User demand will guide the rate of adoption of AVs, including both the rate of purchase of privately owned vehicles (POVs) and shared AVs, the rate of transition of VMT from human-operated vehicles to AVs, and the future of other modes, such as non-motorized modes and traditional public transit.

The uncertainties were presented in a poster at the 2017 Automated Vehicle Symposium (Smith et al., 2017). This poster was also shared informally in July of 2017 during the International System Dynamics Conference (ISDC) in Cambridge, MA. One commenter there suggested adding the impact of a potential well-publicized negative incident to the list of uncertainties, especially when considering these uncertainties from the perspective of potential 'tipping points' in a system dynamics model.

These factors will affect AV launch and adoption in several ways. For example, the scope of the operational design domain for driverless operation depends on technology, and will affect how users will respond. The cost of automated vehicles will depend on technology and policy factors. The rate of AV adoption depends on technology, users, and policy. It will also be affect, and be affected by, AV cost. The decision to share AVs will depend on technology, user and policy factors, as well as the cost of AVs. Finally, policy factors may encourage or discourage technology development.

With the uncertainty surrounding automated vehicles, a further look at each factor was deemed necessary. The next chapter (section 2.5) explores some of the uncertainties relating to travel behavior.

1.5 Remainder of this Report

The following chapters detail our research on selected impact areas: travel behavior, safety, vehicle operations, and energy/emissions. Each of these chapters presents a detailed description of our modeling efforts to date. The report concludes with a brief discussion on our initial concepts around the impact area socio-economics (economy and jobs).

Chapter 2 Travel Behavior

Travelers are likely to respond to the mobility impacts of AVs by changing their behavior. There is an entire field of study on the modeling of demand for transportation. An assessment of the user response to automation found below draws on previous efforts in the field of transportation demand modeling. This chapter is structured as follows:

- Section 2.1 provides a short introduction to choice modeling as currently practiced
- Section 2.2 presents current practice in vehicle ownership models
- Section 2.3 presents current practice in mode choice models
- Section 2.4 discusses potential automated vehicle impacts

It is important to note that the project is currently focusing on passenger transportation, with the “user” being an individual traveler or household. The comments in this chapter apply to both activity-based and trip-based models. Given that higher levels of automation will have far-reaching impacts on travel patterns, it is likely that activity-based or agent-based models will be required to ensure sufficient fidelity to traveler behavior.

2.1 Basics of Choice Modeling

This section presents the basics of disaggregate mode choice modeling, adapted from the work of (Koppelman & Bhat, 2006).

There is a decision-maker, an individual traveler or a household. In the long term, the decision-maker decides whether to purchase an automobile. In the short term, the decision-maker decides how to make a trip: by automobile, public transit, or another way.

Important attributes of the decision-maker, usually considered in models, include:

- Home location
- Work location
- Household income
- Household car-ownership, related to the number of workers and number of adults in the household. This last attribute may be the output of a car ownership model, or an input to a mode choice model.

Additional attributes of an individual decision-maker include sex, age, and employment status.

In a mode choice model, transportation alternatives may include private automobile, bus, train, ferry, bicycling, and walking. The alternatives also have attributes. For a travel mode on a particular trip, these attributes may include:

- Travel time (in and out of the vehicle)
- Travel cost
- Walk access distance
- Transfers required
- Crowding; seat availability
- Frequency of service
- Reliability of service

The attributes of the decision-maker may also interact with the attributes of alternative transportation modes. For example, a high-income decision-maker may be less sensitive to increases in travel cost.

In order to predict mode choice, the decision-rule is that of utility maximization, $U_{it} = V_{it} + \varepsilon_{it}$, where

- U_{it} is the true utility for alternative *i* to decision-maker *t.* The decision-maker chooses the alternative that maximizes U_{it}.
- V_{it} is the deterministic portion of the utility for alternative *i* to decision-maker *t.* It is based on observable attributes, such as travel time.
- ε_{it} is the error term, the portion of the utility that is not observed. This is drawn from a standard extreme value (Gumbel) distribution. The error terms are assumed to be independent and identically distributed across the alternatives.

In a multinomial-logit formulation, the probability of choosing alternative i is given as

$$\Pr(i) = \exp(V_i) \,/\, \Sigma\,(\exp(V_j))$$ (summation over all alternatives j)

2.1.1 Some Examples

Example 1: Auto / Bus

Consider the choice between automobile and bus, where the observed attributes include travel time and cost. Furthermore, we have estimated the following coefficients for travel time and cost:

- Travel time (minutes): -0.03 (negative because more travel time reduces the utility)
- Cost (dollars): -0.6

The travel time is 20 minutes for the automobile, and 25 minutes for the bus. Cost for each is $2. Then

$V_{auto} =$ -1.8 = -0.03 * 20 minutes + -0.6 * 2 dollars, and

$V_{bus} =$ -1.95 = -0.03 * 25 minutes + -0.6 * 2 dollars,

The choice probabilities are

$$\Pr(auto) = 0.54 = \exp(-1.8) \,/\, (\exp(-1.8) + \exp(-1.95))$$
$$\Pr(bus) = 0.46 = \exp(-1.95) \,/\, (\exp(-1.8) + \exp(-1.95))$$

Example 2: Add a second bus

Now, imagine that a second bus (a blue bus) alternative has been added with a travel time of 26 minutes. The second bus's pick-up point is different from that of the original bus, thus travelers cannot simply wait for the first bus that arrives; they must choose to wait for one or the other. Otherwise, its characteristics are the same as for the original bus. The deterministic utility and choice probability calculations are then as follows:

$V_{auto} = -1.8 = -0.03 * 20$ minutes $+ -0.6 * 2$ dollars,

$V_{bus} = -1.95 = -0.03 * 25$ minutes $+ -0.6 * 2$ dollars,

$V_{blueBus} = -1.98 = -0.03 * 26$ minutes $+ -0.6 * 2$ dollars

$\Pr(auto) = 0.37 = \exp(-1.8) / (\exp(-1.8) + \exp(-1.95) + \exp(-1.98))$
$\Pr(bus) = 0.32 = \exp(-1.95) / (\exp(-1.8) + \exp(-1.95) + \exp(-1.98))$
$\Pr(blueBus) = 0.31 = \exp(-1.98) / (\exp(-1.8) + \exp(-1.95) + \exp(-1.98))$

This is, of course, a nonsensical result. Given that the unobserved attributes of the blue bus are the same as those for the original bus, we would expect the new bus to draw riders from the original bus, and not from the auto mode. It comes from the violation of the assumption that the error term is independent between these two alternatives. For more information, readers are invited to review (Koppelman & Bhat, 2006), or to use their favorite search engine to look for “Red Bus Blue Bus paradox” or ”Independence of Irrelevant Alternatives.” (IIA)

Example 3: Nested Logit

Modelers typically deal with the IIA problem by grouping similar alternatives into nests, and calculating the choice probabilities for each nest, and then rolling up to an overall result. The log sum parameter µ is greater than 0 and less than 1, and indicates the dissimilarity within each nest.

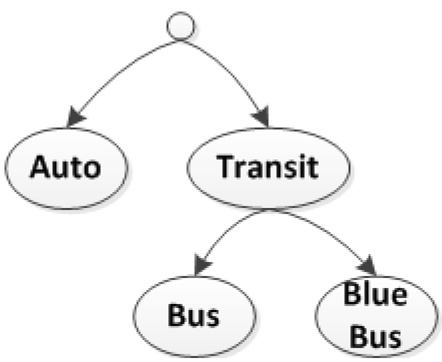

Figure 3: Nested Logit Example

Within the nest:

$\Pr(i) = \exp(V_i / \mu) / \Sigma\, (\exp(V_j / \mu))$ (summation over all alternatives j within a nest)

$V_{transit} = \ln(\Sigma\, (\exp(V_j / \mu))$ (This is the log sum, the overall utility of the alternatives within the nest.)

Choice probabilities for the top level nest are calculated as they were before.

Using these equations, the deterministic utilities (V) and choice probabilities (Pr) under various values of µ are as follows:

Table 1: Nested logit example

	μ = 0.01		μ = 0.5		μ = 0.99	
Alternative	V	Pr	V	Pr	V	Pr
Auto	-1.8	0.54	-1.8	0.45	-1.8	0.37
Transit	-1.95	0.46	-1.62	0.54	-1.27	0.63
Bus	-1.95	0.44	-1.95	0.28	-1.95	0.32
Blue Bus	-1.98	0.02	-1.98	0.26	-1.98	0.31

When μ is small, the new type of bus has little effect on the mode choice. The probability of choosing transit is almost the same as that of choosing the bus in the auto-bus choice in Example 1. When μ is large, it indicates that the 2 types of buses are dissimilar in their unobserved attributes, making their combination more attractive than each would be individually. The choice probabilities are similar to those in Example 2.

These concepts are important to automation in two ways. First, the log sum provides an overall expected utility of a set of alternatives. By estimating the difference in log sums between a set of alternatives with automation, and without automation, one can begin to understand, in a quantitative way, the user benefits from having automation options.

Second, automation is likely to lead to a number of new travel choices: private AVs, shared AVs, shared rides in AVs, and so on. As the number of travel choices increases, it becomes more important to understand their similarities and differences from the user perspective (the unobserved attributes), so that their user response impacts may be correctly modeled.

2.2 Vehicle Ownership Models – Current Practice

Ownership of a privately owned vehicle (POV) can be viewed as a rent or buy decision. If the decision-maker is seeking to maximize utility, factors that are likely to enter the vehicle ownership decision include those shown in Table 2.

Table 2: Factors affecting vehicle ownership

Factors increasing the likelihood of vehicle ownership	Factors reducing the likelihood of vehicle ownership
High disposable income	High capital cost for the vehicle
High number of trips where POV is the best option	Low number of trips where POV is the best option
Vehicle is needed to store goods (tools, materials, etc.)	High walk-bike availability
Owners can receive income by sharing their vehicles	High transit availability
Alternatives (transit, shared vehicle) have low availability	High shared vehicle availability
Alternatives (transit, shared vehicle) have high cost	High cost and inconvenience of parking

Most logit models that predict vehicle ownership do not explicitly consider the availability of shared vehicles. Rather, the individual decision to purchase or not to purchase a car comes from the comparative utility of trips with and without a car. This utility, however, could be affected by the availability of a shared vehicle or shared ride.

In a report on the state-of-the-practice in vehicle availability modeling (as of 20 years ago), (Cambridge Systematics, 1997) described the relationship between vehicle ownership, trip making and mode choice. The output is vehicles per household. Typical inputs included:

- Persons per household
- Workers per household
- Household income
- A variable representing the type of land use at the household (urban area, single/multi-family, etc.)

In 1997, the use of accessibility measures and the quality of the pedestrian environment was considered to be advanced practice. Shared vehicles or rides are not mentioned.

15 years later, NCHRP report 716 (NCHRP, 2012) provided an overview of the state-of-practice in all areas of demand modeling, including vehicle availability. It presented the following examples of decision variables:

- Household characteristics:
    - Persons per household;
    - Workers per household;
    - Household income; and
    - Single or multifamily dwelling.
- Geographic (zone) characteristics:
    - Urban area type;
    - Residential and/or commercial density; and
    - Pedestrian environment.
- Transportation accessibility:
    - Accessibility via highway;
    - Accessibility via transit; and
    - Accessibility via walking/bicycling.

With vehicle availability modeling, households can be segmented into vehicle availability levels. Examples are:

- No vehicles
- Fewer vehicles than drivers
- Equal number of vehicles and drivers

We also reviewed auto ownership models from two MPOs: Puget Sound Regional Council and Atlanta Regional Commission.

Puget Sound Regional Council (Bowman, Bradley, & Childress, 2015) presented an auto ownership model that included the following variables:

- Number of drivers in the household
- Whether there are at least as many cars as workers
- Part-time workers per driver
- Elderly adults per driver
- University students per driver
- Driving age children per driver
- Children under 5 per driver
- Household income category (less than $15K/year, $15-$30K, $30-75K, more than $75K)
- Log distance to transit stop

- Number of transit stops in the household buffer (near the household)
- Tour mode choice log sum for work travel with and without auto - this is a measure of accessibility (transit quality), with and without automobile
- Tour mode choice log sum with and without auto for students
- Distance to nearest transit stop less than 0.5 miles
- Log of food, service, retail and residential employment density

The Atlanta Regional Commission activity-based model specification (Atlanta Regional Commission, 2012) had similar explanatory variables, including

- Household size and composition
- Income
- Parking cost and density in residential zone
- Peak mode choice log sums to work for all workers
- Destination choice log sum for residential zone

Although car sharing availability has not been explicitly considered in auto ownership models, a number of variables in these models are strongly correlated to car sharing. For example, car sharing tends to be more prevalent in places with high parking cost, high density, and high transit accessibility.

Today, a fundamental limitation with car sharing is that of access to the vehicles. Since the vehicles cannot deliver themselves, they need to be located where there are high concentrations of potential users: transit hubs, densely populated residential neighborhoods, universities, or employment centers. As a result, although car sharing is experiencing rapid growth, it is still a niche market. The 1.1 million car share members (Shaheen, Chan, Bansal, & Cohen, 2015) in the U.S. are only a small fraction of the adult urban population.

Other research, cited in (Shaheen et al., 2015) points to a significant effect of car-sharing on vehicle ownership and usage and, consequentially, on mode share. For a household, the availability of a car-share vehicle provides a viable option for those trips that require an automobile, enabling fewer vehicles to be owned. On the other hand, the higher marginal cost of using the car share vehicle, as opposed to an owned vehicle, make it less likely that the car share vehicle will be used for trips that can be handled by walking, bicycling, or public transit.

2.3 Mode Choice

The typical state-of-practice is to use a nested logit model for mode choice, often with separate coefficients for differing trip types. For example, a home-to-work trip might use different coefficients than a home-to-shopping trip. Observed attributes of the choices that commonly appear include:

- An alternative-specific constant, used to adjust model results to better reflect observed choices
- In vehicle travel time (IVTT). In New Starts guidance, FTA has indicated that “compelling evidence” is needed to use a coefficient of IVTT that falls outside the range of -0.02 to -0.03, when IVTT is measured in minutes (NCHRP Report 716)
- Out of vehicle travel time (OVTT). In New Starts guidance, FTA has indicated that “compelling evidence” is needed to use a coefficient for OVTT that is not two to three times larger than the coefficient for IVTT (NCHRP Report 716). OVTT includes waiting, transfers and walking to and from the vehicle.
- Cost, which is the out-of-pocket cost (e.g., transit fare or fuel for an automobile)

In a number of models, OVTT is split into its components. It is commonly recognized that transfers between vehicles are disliked by riders, and may have a penalty, either explicitly, or via the OVTT parameter.

Where a model does not use a particular coefficient, it is marked n/a in the table.

Table 3 adapted from Table 4.8 of (NCHRP, 2012), illustrates examples of coefficients used in MPO travel demand models. The time variables are in minutes and the cost variables are in dollars in this table. Where a model does not use a particular coefficient, it is marked n/a in the table.

Table 3: Examples of mode choice coefficients

Model	IVTT	OVTT	Walk Time	First Wait Time	Transfer Time	Cost
A	-0.021	n/a	-0.054	-0.098[9]	-0.098	-0.31
B	-0.030	-0.075	n/a	n/a	n/a	-0.43
C	-0.036	-0.053	n/a	n/a	n/a	-0.77
D	-0.019	n/a	-0.058	-0.081	-0.04	-0.72
E	-0.025	-0.05	n/a	n/a	n/a	-0.25
F	-0.044	-0.088	n/a	n/a	n/a	-0.67
G	-0.028	-0.065	n/a	n/a	n/a	-0.55
H	-0.033	n/a	-0.093	-0.038	-0.038	-0.21
I	-0.025	-0.05	n/a	n/a	n/a	-0.5[10]

2.4 Potential Automated Vehicle Impacts

Automated vehicles may affect both vehicle ownership and vehicle use.

2.4.1 Vehicle Ownership

The impact on vehicle ownership rates is unknown and will be linked to the availability of automated vehicles? If AVs make shared vehicle options more widely available and more attractive, it may become less necessary to own a personal vehicle. On the other hand, automation may make "driving" more convenient and encourage vehicle ownership. The numerous predicted impacts are summarized in Table 4:

[9] Model A uses a first wait time stratified by the first 7 minutes and beyond. The coefficient shown is for the first 7 minutes; the coefficient for beyond 7 minutes is –0.023.
[10] Model I has a separate coefficient for auto parking cost, which is –0.25; the coefficient shown is for all other auto operating and transit costs.

Table 4: Some ways in which AVs could reduce, not affect, or increase vehicle ownership rates

AVs could reduce vehicle ownership	AVs would not affect vehicle ownership	AVs could increase vehicle ownership
• Because shared cars can deliver themselves to the passenger's door: o Car sharing may become available in less dense areas o Car sharing may become more convenient everywhere • Capital cost of AVs may be higher than human-driven vehicles (at least initially), thus encouraging sharing	• Some vehicle users – such as home improvement contractors – store many items in their vehicles and cannot practically share vehicles	• Persons who currently cannot hold a driver's license (certain disabilities; age (young or old); etc.) could have their own vehicles • Persons without convenient parking could own a vehicle and send it to park itself elsewhere

Note, however, that the possibilities in the last column may also encourage the use of shared AVs, and thus increase vehicle use but not ownership rates of dedicated vehicles.

These and other factors are presented on a diagram of impact linkages, as shown in Figure 4. This approach is inspired by (Milakis, van Arem, & van Wee, 2017).[11] Green arrows, with plus signs, indicate that an increase in the item at the origin of the arrow would tend to lead to an increase in the item at the arrow's destination. Red arrows, with minus signs, indicate instead a general negative causation. Identifying these impact linkages at a high level are an initial step towards further more-detailed analysis using system dynamics principles.

[11] That paper includes a very large impact linkage diagram showing first, second and third-order impacts of automated vehicles, rather than the more detailed diagrams of part of the system, as shown here. The terminology of 'zero time-cost' in our diagram comes from (Milakis, van Arem, & van Wee, 2017)

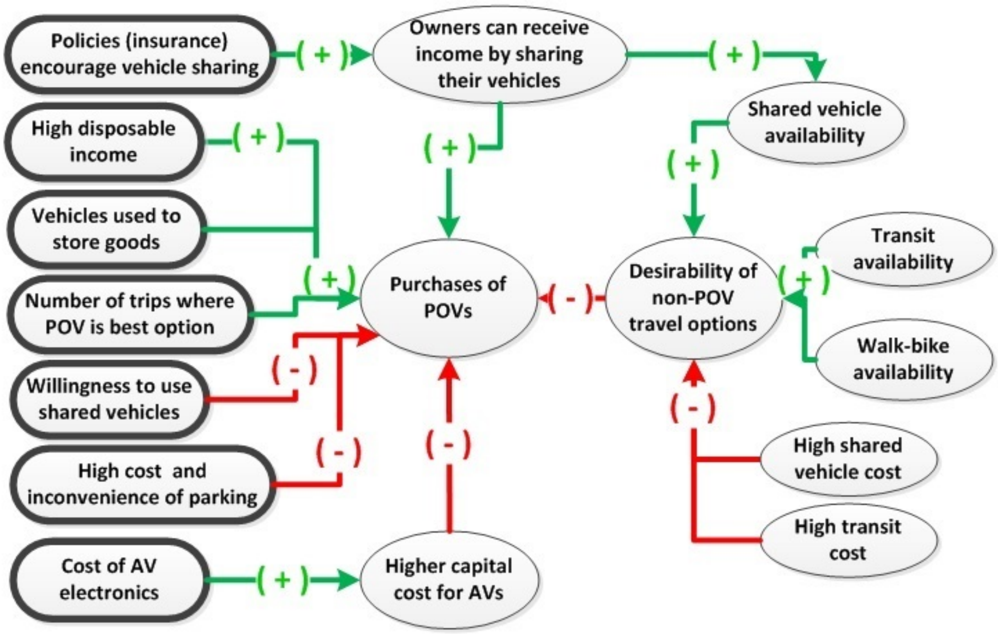

Figure 4: Impact linkage diagram for privately owned vehicle (POV) purchases

2.4.2 Vehicle Use

Table 5 summarizes ways in which AVs could affect vehicle use – either in terms of number of trips, or VMT. It is important to note that we assume that L4 or L5 AVs are capable of travelling with no human on-board – the so-called 'zero-occupant' trip.

Table 5: Some ways in which AVs could reduce, not affect, or increase vehicle use

AVs could reduce vehicle use	AVs might not affect vehicle use	AVs could increase vehicle use
• Most car-sharing business models offer a higher marginal cost and lower fixed cost than car-ownership models. If AVs are primarily furnished via a car-sharing business model, overall vehicle use might be reduced. This is especially true if trips are shared, with several riders in each vehicle.	• Some zero-occupant trips would not affect total VMT much – for example, when a shared AV drives itself from drop-off of one passenger to the requested pick-up point of the next. This is equivalent to a taxi driver 'deadheading' to pick up the next fare. Although total trips in shared vehicles might increase, the possibility of having optimal dispatch algorithms could result in fewer overall miles driven than when each driver has a dedicated vehicle.	• Time cost of vehicle operation decreases when cars can 'run errands' themselves - zero-occupant trips o For example, a contractor could buy a dedicated AV, then send it to pick up supplies while continuing to work o AV owners could direct their vehicles to park in lower-price parking on the outskirts of the city, then summon them to return for pick-up • Persons who currently cannot hold a driver's license could travel more conveniently, without depending on a friend, relative, bus or paratransit service

Figure 5 shows the impact linkage diagram for vehicle use.

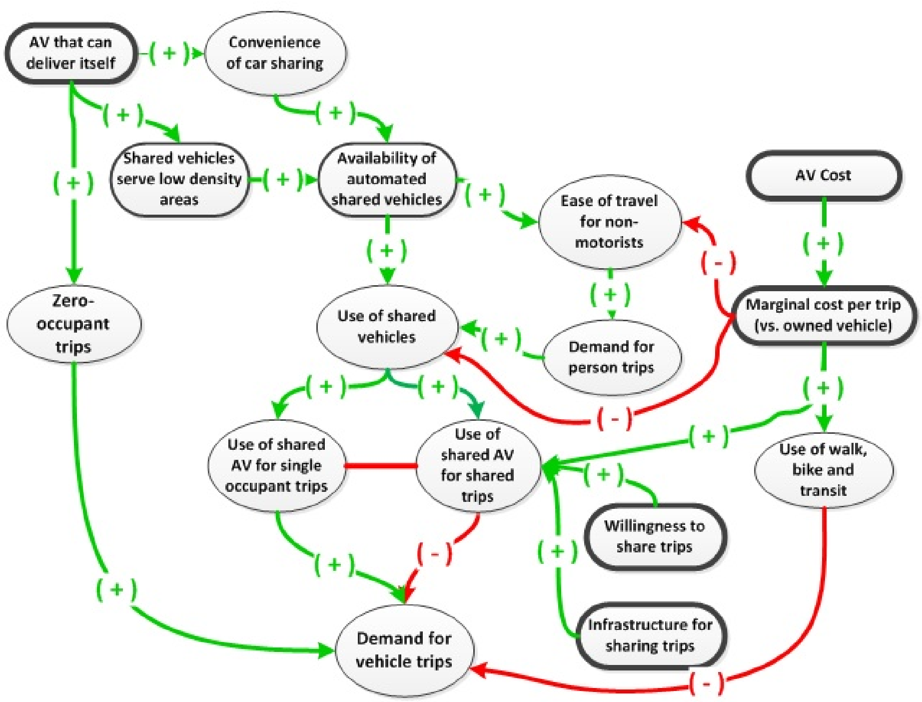

Figure 5: Potential effects of AVs on vehicle use

2.4.3 Resulting Impacts on Travel Behavior

The potential impacts of AVs on travel behavior, and thus vehicle miles traveled, can be summarized as follows.

At the lower levels of automation, where a driver is still required, or where a level 4 automated vehicle is operating on a fixed route, the impacts are likely to be modest. "Driving" may become more convenient, thus reducing the value of IVTT for those using the vehicles. New automated transit options may become economically feasible.

When automation reaches the point of technological and policy development where vehicles can reposition themselves without a driver, the impacts could be far-reaching. One could envision three scenarios. They are not mutually exclusive.

1. Vehicles continue to be privately owned and not shared except within a household, much as they are today. The marginal cost per trip is still low, as it is today for a POV. If the occupant of the vehicle can engage in tasks other than driving, the value of IVTT decreases. Furthermore, if a vehicle can reposition to an area where parking is inexpensive, the disincentive of high parking costs at some destinations goes away. Fewer vehicles may be owned, as a single vehicle can more easily serve multiple members of a household via self-repositioning[12] however, one would expect VMT to increase under this scenario.

2. Vehicles are shared, but trips are not shared (except within a household). This is similar to the car-sharing that exists today, with the important difference that vehicles are able to deliver themselves to users. There is a moderate cost per trip (because the capital cost of the vehicle has to be covered); therefore transit, walking, and biking options may become more attractive for short trips. Vehicle utilization will be higher; therefore fewer vehicles will be needed, which will reduce the needed space for parking. If vehicles are powered by internal combustion engines, there will be fewer cold-starts, with a beneficial effect on emissions. The overall effect on VMT is unclear: there will be zero-occupant trips, but the higher marginal cost per trip (compared with privately owned vehicles), which may encourage more walking, biking, and transit trips.

3. Vehicles and trips are shared. This is parallel to some of the shared ride services (e.g., UberPool, Lyft Line) that exist today. Compared to the previous scenario, the cost per trip is slightly lower, but the service is less convenient (the rider is sharing the vehicle with strangers and may need to detour slightly for their pick-ups and drop-offs). Overall effect on VMT will likely be a decrease.

2.5 Impact Mechanisms

Our team has begun developing detailed 'maps' of the interactions shown in Figure 2. We believe that two important questions relate to vehicle sharing and trip sharing:

- Will automated vehicles be individually owned, or accessed via a shared-ownership model, much as car-sharing services work today?
- Will trips be shared; that is, will strangers share a ride when they have compatible origins and destinations?

[12] see (Schoettle & Sivak, 2015)

Figure 6 considers the first question by focusing on the impact of several factors on the decision to purchase a POV[13] versus to use another option: shared vehicles, transit, or non-motorized modes. In this use case, we assume that a shared AV can deliver itself to the rider's trip origin (for trips beginning on roads that are within the vehicle's ODD), and also take its rider to at least some destinations without the rider needing to be a qualified driver. Riders pay per hour (or perhaps per mile or kilometer) without a significant up-front capital cost.

Figure 6 examines a few of the key factors from each of the three categories:

- **Automation technology:** *ability to handle the unexpected,* and *complexity.* These are, respectively, the key drivers of the scope of the ODD for operation without a licensed driver, and of the cost of the on-board electronics required, which in turn affects overall AV capital cost. Links from and among these factors are shown in purple, with signs indicating the polarity.
- **Policy:** *incentives, cost structures, infrastructure decisions,* and *allocation of right of way.* In order to analyze the effects of these sorts of policies we must evidently be more specific; for the sake of this example, we assume that these are policies and decisions which encourage shared fleets and which affect the cost and inconvenience of parking. Links from policy factors are shown in blue.
- **User response**: *willingness-to-pay in a many-option environment, willingness to use shared vehicles,* and *willingness to share rides*. Links from user response factors are shown in brown.

Feedback among the other dependent variables is shown in green (positive (reinforcing) feedback) and red (negative (balancing) feedback).

[13] While the intention of Figure 6 is to show the factors influencing purchases of privately-owned AVs vs. use of shared AVs, many of the feedback mechanisms also apply to the decision to purchase any POV (even non-automated) in a world in which shared AVs are available.

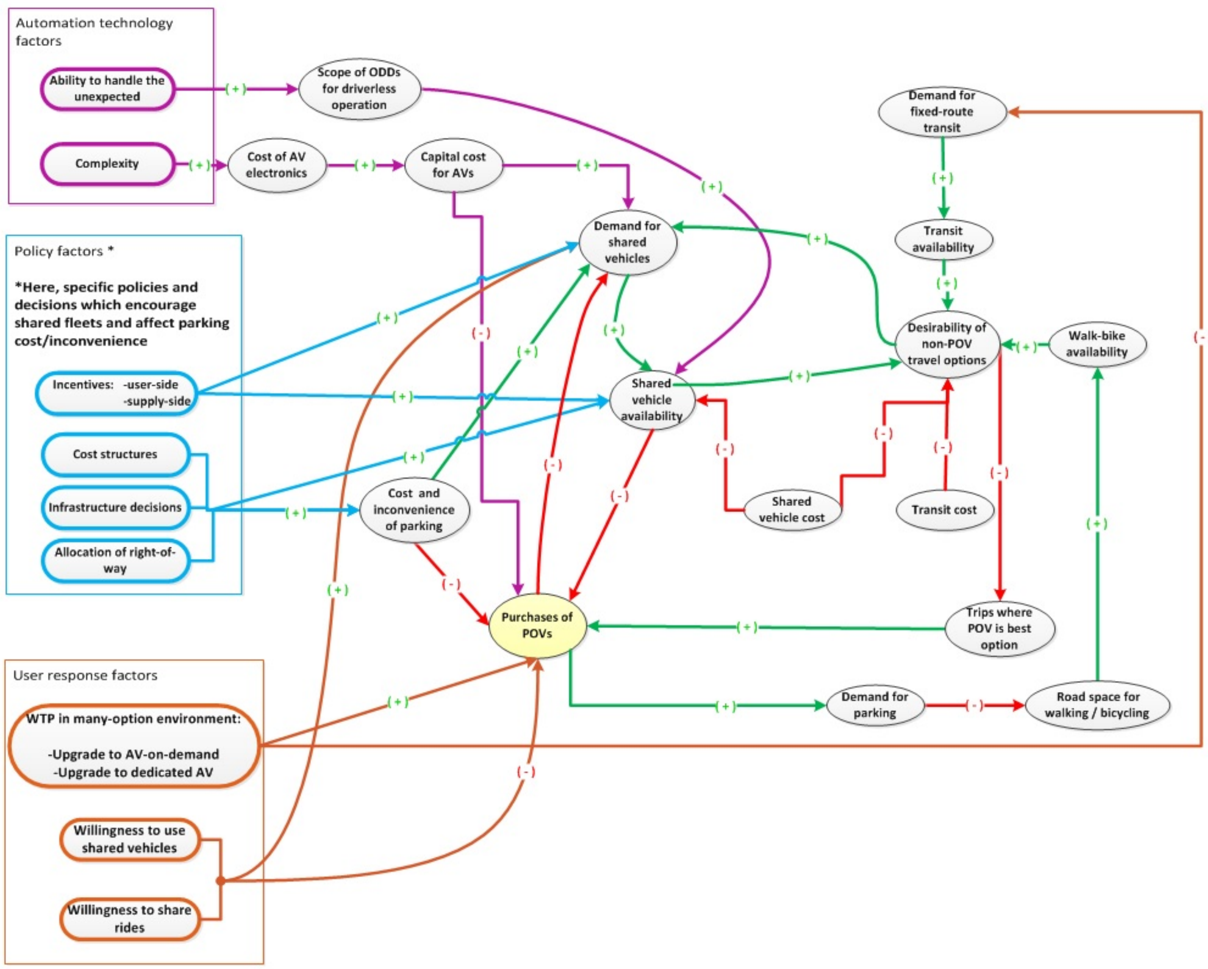

Figure 6: Effects of key factors on purchases of POVs

Automation technology factors: If better technology in Level 4 AVs means that they can better handle the unexpected and function without a licensed driver in broader ODDs, they will be able to deliver themselves to more trip origins. This will tend to increase their availability; this availability then increases the desirability of non-POV options, which in turn increases demand. Increased demand boosts availability, completing the positive feedback loop. If AVs require more complex technology to function, this will also tend to increase their cost, which could further encourage demand for shared vehicles and depress purchases of POVs.

Policy factors: Incentives targeted towards end users of shared AVs (user-side incentives) would increase demand for shared vehicles, while supply-side incentives would tend to increase shared vehicle availability. Cost structures, infrastructure decisions and right-of-way allocation policies could (if of the types assumed above) all both increase the availability of shared vehicles and make parking more expensive and less convenient. More difficulty in parking would tend to decrease purchases of POVs, as would greater availability of shared vehicles.

User response: A willingness to pay to upgrade from fixed-route transit to a shared AV on demand would tend to depress demand for traditional fixed-route transit, while willingness to pay to upgrade to a dedicated AV would boost purchases of POVs. Both increased willingness to use shared vehicles and increased willingness to share rides with other passengers in an AV would increase demand for shared AVs and independently decrease purchase of POVs. (Does not specifically consider demand for shared rides.)

Observations from looking at the interactions among the adoption and deployment variables themselves include:

- *There is a positive feedback loop for purchases of POVs; by reducing the amount of space available for non-motorized modes they make these other modes less desirable.*

  More purchases of POVs lead to more demand for parking, which reduces the rate at which road space is repurposed for walking or cycling and may even lead to its return to a parking use. That in turn can reduce the availability of walking or biking, which would contribute to a reduction in the desirability of travel options without a POV. This decrease means that there would be more trips for which a POV is the best option; and thus, would tend to lead to an increase in purchases of POVs.

- *Conversely, increased demand for shared vehicles, coupled with increased availability of shared vehicles may also be self-reinforcing*.

  This is because increased availability increases the desirability of non-POV travel options. A larger loop leads to the same outcome via another mechanism: that increased desirability of non-POV options means that there are fewer trips for which POV is the best option, and that will tend to depress POV purchases. When fewer people own POVs there is likely to be greater demand for shared vehicles.

- *However, the world of many services at many price-points (referred to as a so-called "heaven" scenario in* (Chase, 2014) *could, under certain conditions, lead to a swing back towards the "hell" world where each family has its own AV*.

  This is because increased willingness to pay for marginal service level improvements over fixed-route transit can lead to less demand for and then a reduction in the availability of such transit. That would tend to render non-POV options less desirable, leading to an increase in the portion of trips where a POV is the best option, and an accompanying increase in purchases of POVs.

This exploration of the impact mechanisms suggests how a system dynamics approach could reveal potentially important concerns about AV adoption and deployment. Policy makers and car-sharing companies may need to consider whether a launch of an automated shared vehicle service in a given area is likely to generate enough customers to be sustainable. There may be a scenario in which demand for those shared AVs was strong enough to lead the local transit authority to cut fixed-route service, but not strong enough for the car-sharing firm to decide to keep the new service operating, at least with the level of service and prices that drove its initial expansion of market share. What began as an attempt to provide additional transport options might end up leaving residents with fewer options other than a POV. The exact inflection points in terms of pricing, operational level of service, etc. are clearly worth additional consideration before the new service launches. This sort of particular sensitivity would be hard to spot without a system dynamics approach.

Figure 7 examines the second question introduced in this section by looking in more detail at the dynamics of shared AVs. The figure also links these more detailed impact linkage diagrams back to the overall societal outcomes shown in the Framework presented in Figure 1. It will look in more depth at a shared AV that can deliver itself, and considers the factors making it more or less likely that trips will be shared, as well as related impacts. Technology factors, such as cost, are outlined in purple. Factors relating to both technology and policy are outlined in dark blue. Factors relating to policy are outlined in light blue, and factors relating to user response are outlined in orange.

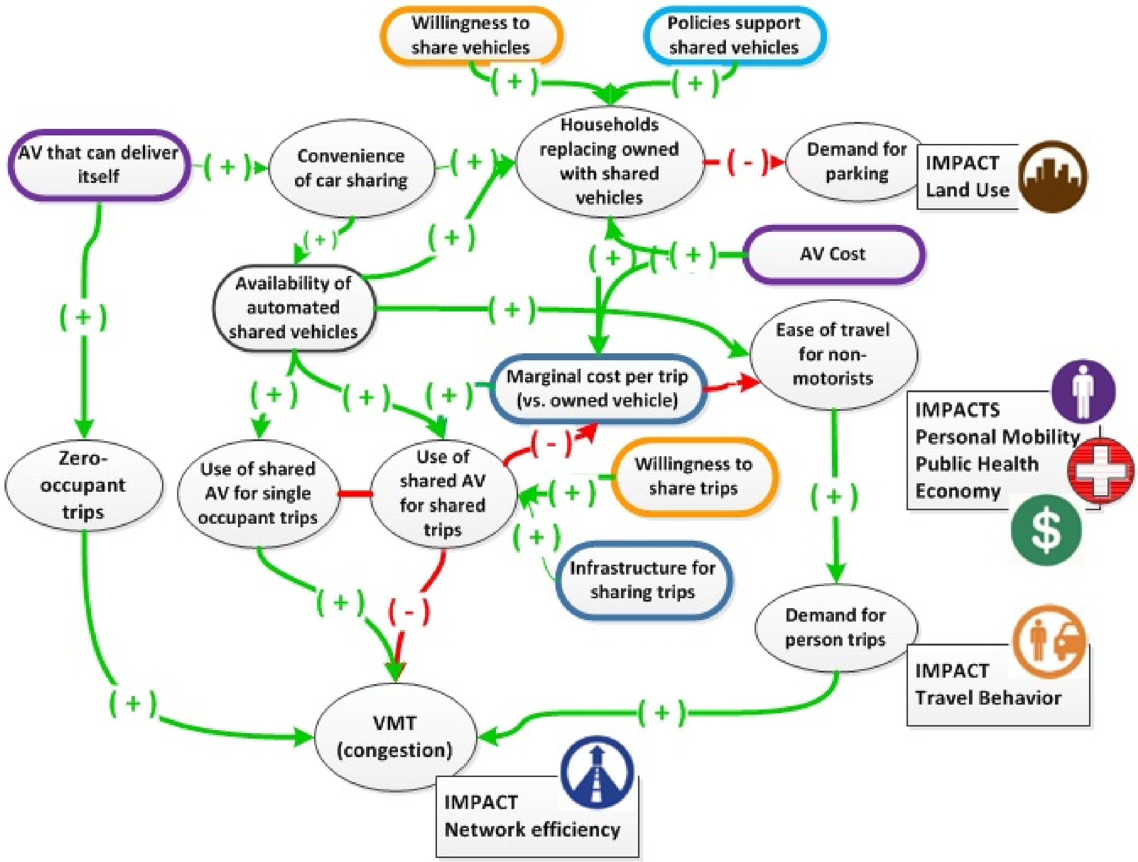

Figure 7: Shared AV impact linkages

An AV that can deliver itself will significantly increase the convenience of car-sharing. This can lead to an expansion of the car-sharing market, with greater availability of automated shared vehicles. It may also lead to more households replacing privately owned with shared vehicles, thus leading to reduced demand for parking, which is a significant infrastructure and land use impact. (Owned vehicles are typically idle most of the time, while shared vehicles have higher utilization, with fewer of them needed to meet travel demand.) [14]

Greater availability of automated shared vehicles that do not need a qualified driver will provide more travel options for non-motorists.[15] This has a number of impacts including:

[14] Several papers have suggested that one shared vehicle could replace approximately ten owned vehicles, e.g., ((Fagnant & Kockelman, 2015), (OECD/International Transport Forum, 2015)

[15] This is expected particularly in areas not well served by traditional public transit. It is subject to the risks raised in the preceding discussion of potential reduction of travel options under certain circumstances in places in which fixed-route transit is currently offered.

- Personal mobility (non-motorists are no longer limited to often meagre transit options)
- Public health (non-motorists may more easily access medical care and recreational activities; on the other hand, there may be reduced use of walking and bicycling)
- Economy (non-motorists may more easily access jobs)

All of these may lead to an increase in person trips, tending to increase overall VMT, which may mean greater congestion on the transportation network.

Compared with non-automated car sharing, zero-occupant trips as the vehicles deliver themselves will tend to increase VMT partially. (The point that shared AVs may generate less VMT than POVs is outside the scope of Figure 7.)

A significant difference in the cost structure between owned and shared vehicles (at least as business models for purchase, registration, insurance, etc. currently work in the U.S.) is that owned vehicles have a relatively high fixed cost (e.g., depreciation, insurance, registration fees, some maintenance), with a low marginal cost (e.g., fuel). This means that once the vehicle is purchased, the marginal cost of using it is low, as the purchase cost has already been incurred, whether or not the vehicle is used. Therefore, the owned vehicle tends to be used for many trips. On the other hand, a shared vehicle has a low fixed cost (typically, a $25-$100 annual membership fee), with a higher hourly cost of use (in the $10/hour range). This makes it more likely that the person who depends on a shared vehicle will use transit, walking or bicycling for trips where those modes are convenient. If capital costs for AVs are higher than current vehicle costs, this will also tend to increase the marginal cost per trip in a shared vehicle environment.

The question of solo versus shared *trips* is treated in the middle of the diagram. If the marginal cost per trip is high, there will be an incentive for users to share trips, in order to share the cost. If more trips are shared, then the marginal cost per user per trip will decrease.

Other factors that go into the use of shared AVs for shared trips include the user willingness to share trips, independent of the cost considerations. Will someone get into a car with a stranger? Infrastructure for sharing trips, such as ride-matching apps, also impacts the quantity and willingness of users to share trips.

Finally, more shared trips will tend to decrease VMT, due to serving several travelers in each vehicle.

Chapter 3 Safety

Safety should be measured using actual crash data from naturalistic baseline and treatment driving test conditions (i.e., drivers unassisted versus drivers assisted with advanced vehicle applications). However, when vehicle technology is new and not yet widespread (or even present) in the on-road fleet, actual crash data from real-world driving simply are not available to use because crashes have not yet occurred and cannot be accounted for without equipped vehicles on the roads. Moreover, crash data are rare or non-existent during the execution of naturalistic driving field operational tests since widespread exposure is required to ensure adequate crash data. The scope of field operational tests is typically limited to a few instrumented vehicles driven by volunteer subjects for a relatively short period of time. Nevertheless, finding a way to assess the safety benefits of such emerging technologies is vital to ensure that deployment provides a public benefit.

3.1 Basic Safety Benefits Equation

This Framework describes a methodology to incorporate driver/vehicle/system performance data from various sources (e.g., a non-crash driving environment such as field operational tests, objective testing, human factors testing, and historical crash data) into a benefits model so that potential safety benefits of advanced vehicle applications can be projected.

$$\boldsymbol{B = N \times E} \qquad \textbf{(1)}$$

Where:

$\boldsymbol{B} \equiv$ Reduction in annual baseline target crashes in a scenario by an application

$\boldsymbol{N} \equiv$ Annual number of baseline target crashes in a scenario

$\boldsymbol{E} \equiv$ Crash avoidance effectiveness of an application in its target scenario

Information for the annual number of baseline target crashes, ***N***, can come from historical crashes from national databases or observed crashes in field operational tests. Target crashes should be tailored to specific ODDs in which an advanced vehicle (e.g., crash avoidance) application may apply. A recently completed task developed and implemented a method to determine preliminary estimates of baseline crashes for emerging concept automated vehicle functions (Yanagisawa, Najm, & Rau, 2017). This task will be described briefly in subsequent sections. The results from this study serve as the basis for providing part of the data necessary for estimating potential safety benefits of automated vehicles and their specific functions. The final component of the benefits equation requires further driver/vehicle/system performance data and research in order to accurately quantify benefits.

This Framework further describes and begins the process of estimating potential safety benefits. However, given the current state of the US vehicle-fleet, the Framework will focus on quantifying the crash avoidance system effectiveness estimate, ***E***[16]***.*** This value is broken down into two safety components as described in Equation (2) below:

$$\boldsymbol{E = 1 - Exposure\ Ratio \times Prevention\ Ratio} \qquad \textbf{(2)}$$

[16] As noted earlier, with limited deployment of automated vehicle technologies, providing very limited number of crashes, surrogate measures from various sampled data sources and non-crash conflicts are used to estimate potential benefits.

The driving conflict[17] ***Exposure Ratio*** is the ability of an advanced vehicle application to reduce the occurrence of conflicts in normal driving behavior (McMillan & Christiaen, 2001) Driving conflicts correspond to the kinematics of target pre-crash scenarios that represent vehicle movements and orientation, as well as the safety-critical event immediately prior to the crash. This represents the ability of an automated vehicle to avoid crash conflicts in normal driving conditions (e.g., driving within the specified ODD). The crash ***Prevention Ratio*** is the ability of an advanced vehicle application to reduce the likelihood of a crash given that a vehicle enters a driving conflict (McMillan & Christiaen, 2001). This represents the automated vehicles ability to avoid an imminent crash through automated control or the timely transition of control from system to driver to successfully avoid an imminent crash.

The individual ratios are derived from driver/vehicle/system performance data both without and with an advanced vehicle application, therefore the equation to estimate crash avoidance effectiveness can be rewritten as shown Equation (3):

$$\boldsymbol{E = 1 - \frac{EM_{with}}{EM_{without}} \times \frac{CP_{with}}{CP_{without}}} \quad \textbf{(3)}$$

EM_{with} ≡ Exposure Measure to a driving conflict corresponding to a target scenario with advanced vehicle application

$EM_{without}$ ≡ Exposure Measure to a driving conflict corresponding to a target scenario in without advanced vehicle application

CP_{with} ≡ Crash Probability when exposed to a driving conflict corresponding to a target scenario with advanced vehicle application

$CP_{without}$ ≡ Crash Probability when exposed to a driving conflict corresponding to a target scenario without advanced vehicle application

The available driver/vehicle/performance data with specific advanced vehicle technology (and similar functionality) that may apply to automated vehicle applications is relatively small. Data can come from various literature, field operational tests, objective testing, and human factors based experiments. Although new automated vehicle data is currently available, it has been relegated by the specific needs of a company and considered propriety and/or in its infancy, making it relatively unavailable. On the other hand, an abundance of research and information has been published by private industry and the USDOT on driving warning applications. The data sets for these driving warning applications can be used as preliminary data sources to exercise the benefits methodology and provide insight on data needs. Further research and collaboration on automated vehicles and their functionality is needed to determine the exposure to driving conflicts with advanced vehicle applications and the crash probability ratio within these conflicts (both with and without technology).

This Framework leverages available resources and algorithms to data mine for exposure to driving conflicts without advanced vehicle applications (i.e., baseline) and quantify crash statistics for baseline crashes in which a theoretical automated vehicle can provide a safety benefit (i.e., a target crash population within the ODD of an automated vehicle to use as a baseline). Further, this Framework investigates, in collaboration with private industry, the affects advanced vehicle applications may have in the treatment condition (i.e., estimate conflict and crash rates with advanced vehicle applications), producing a preliminary estimate on system effectiveness.

[17] Driving conflicts refer to driving events that could result in a crash without proper driver intervention to avoid the crash.

3.2 Target Crash Population

Previous research conducted quantified preliminary target crash population estimates for select concept automated vehicle functions (Yanagisawa et al., 2017). Results from this research provide a baseline target crash population as detailed in Equation (1). Target crash populations for concept automated vehicle functions in light-vehicles were estimated in terms of annual police-reported crash frequency, fatal-only crash frequency, and comprehensive economic costs.[18,19]

The research detailed and exercised a methodology to identify concept automated vehicle functions and their designated NHTSA Automation Level, define appropriate ODDs of these functions, correlate their ODD to crash data, and query national crash data. The methodology developed five query layers to correlate concept automated vehicle function ODDs to crash data; these layers consisted of identifying crash location, pre-crash scenario, environmental conditions, travel speeds, and driver condition. Each concept automated vehicle function was cross-referenced through the crash databases, using these five layers, to identify addressable target crashes. Ten high-level concept automated vehicle functions (NHTSA L2-L4) were identified along with nine lower-level concept automated vehicle functions (NHTSA L0-L1). Results were identified by aggregating specific concept vehicle functions within automation level and quantifying target crash populations. Furthermore, the higher-levels of automated vehicles were quantified using perceived safety benefits from near-term production lower-level automated vehicle concept functions. Research results can be seen in (Yanagisawa et al., 2017) identifying target crash populations for higher-levels of automation using two distinct aggregation methods: (1) assuming higher-levels of automation are independent of one another and (2) assuming higher-levels of automation inherit functionality and benefits from any lower-level concept automated vehicle function.

The research above was conducted using available data sources and information at the time. In support of NHTSA research, it was determined at the time that using NHTSA levels of automation definitions were appropriate. Further, the research was completed in 2015, using crash statistics from the 2013 crash calendar year. Currently, Volpe is updated this research task with updated crash statistics with the latest available dataset (i.e., 2015 crash data) and correlating the crash data to SAE levels of automation.

3.3 Estimating System Effectiveness

This Framework outlines a method to estimate potential safety benefits and system effectiveness of advanced vehicle applications using sources beyond historical crash data. Given the current state of the vehicle fleet and available research data, external data sources are incorporated to estimate system effectiveness as shown in Equation 3. This section describes the current status of using various data sources to estimate the system effectiveness of an advanced vehicle applications.

3.3.1 Defining System Parameters and Operational Design Domain

An initial task in the system effectiveness process is to identify an advanced vehicle application, its functionality, and define an appropriate ODD. The defined functionality and ODD will aid in identifying data sources and developing data mining algorithms. In order to exercise the methodology detailing in this

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[18] Light vehicles are passenger cars, vans and minivans, sport utility vehicles, and pickup trucks with gross vehicle weight rating less than 10,000 pounds.

[19] Comprehensive costs include productivity losses, property damage, medical costs, rehabilitation costs, congestion costs, legal and court costs, emergency services such as medical, police, and fire services, insurance administration costs, and the costs to employers

Framework, an automated highway function with simultaneous longitudinal and lateral control (e.g., adaptive cruise control (ACC) and lane centering/lane keeping technology) was proposed. This system can be classified on various automation levels; however, this analysis will focus on the system as an SAE L2 automated vehicle. The ODD is defined as:

- Light vehicle is the host: the light vehicle is assumed to have the automated vehicle concept functions on board and active.
- System is active on highways only: the system works on properly maintained, high-speed roads with limited access (i.e., no intersections, limited variations in normal driving).
- System can work in inclement weather: the system is negligibly affected by lighting, weather, and surface conditions.
- System would address rear-end, lane-change, and road-departure crashes (at minimum).
- Driver is engaged and active within the driving task (i.e., driver is monitoring driving environment and is responsible for the fallback performance).

The above constraints will help define data sources and data mining algorithms needed to estimate the parameters necessary within the safety benefits equation.

3.3.2 Baseline Conflict Exposure and Crashes

A crucial step in the benefits process is identifying a proper baseline condition. Identifying a proper baseline condition to compare to a treatment condition can be difficult when a treatment condition is not readily defined (one cannot compare vehicle model years when advanced vehicle applications were not standard to situations after they became a standard). As future research plans seek to identify and quantify a treatment condition (e.g., through field test studies, limited production release, and characterization testing), this Framework focuses on identifying and quantifying a proper baseline condition for research plans and benefits assessment.

Baseline conflict exposure can be determined using the Integrated Vehicle-Based Safety Systems (IVBSS) naturalistic driving data. The IVBSS field operational test collected naturalistic driving data from 108 test subjects who drove 16 passenger vehicles equipped with integrated vehicle-based warning applications[20] (Nodine, Lam, Stevens, Razo, & Najm, 2011). For each subject, the test period was divided into a 12-day baseline condition with the applications disabled, and a 28-day treatment condition with the applications enabled. The technology implemented on these prototype vehicles may be similar to technology that may be deployed by current advanced vehicle applications[21] (i.e., vehicle-based radar and camera system quality and algorithms used). The detailed data collected from sensors on vehicles can be used to forecast behavior of advanced vehicle applications using the same input sensor data. This can be done by defining and characterizing operational boundaries of the technology (e.g., issues from vehicle speed and processing time, environmental hurdles, and infrastructure limitations) or simulating advanced vehicle application behavior by superimposing system algorithms onto detailed time-history data.

[20] The IVBSS contained Level 0 (NHTSA and SAE) warning systems, including forward collision warning (FCW), blind spot warning/lane change warning (BSW/LCW), and lane departure warning (LDW).
[21] The proposed advanced vehicle application capability translates directly to the IVBSS applications. Longitudinal control (i.e., ACC) and FCW target rear-end crashes. Lateral control (i.e., lane keeping/lane centering), BSW/LCW, and LDW target lane change and lane drifting/road departure crashes.

The IVBSS data was queried for specific events (e.g., alerts and near-crash conflicts)[22] that could be applicable to the defined advanced vehicle application parameters and ODD. Alerts and near-crash conflicts were selected to identify safety critical events (beyond the normal driving task) that may be encountered by an advanced vehicle application. This query includes the selected criteria below:

- Highway miles driven – the advanced vehicle application would only operate on limited access roads with higher speeds and limited interruption.
    - o Defined by the available road classification variable and selected as "Federal (Interstate) Highway" and "State-Owned Highway."
- Lighting conditions – the advanced vehicle application may be hindered by poor or complex lighting conditions, specifically video based technology and algorithms[23].
    - o Defined by the available daylight variable and determined as "Day" and "Night".
- Weather conditions – the technology may be hindered by adverse weather restricting sensor input (e.g., snow on the ground obscuring lane makers, wet roads creating reflections).
    - o Defined by the vehicle wiper variable and determined as "Off" to be "Clear" and "On" to be "Adverse" weather.

Overall, the participants drove 110,000 miles on highways. As shown in Figure 8, the majority of driving was done under clear conditions during the day. Only 6 percent of miles were driven during adverse weather and 27 percent of miles were driven during the night and potentially lower levels of lighting. This information shows the primary environment in which the proposed advanced vehicle application would most likely operate.

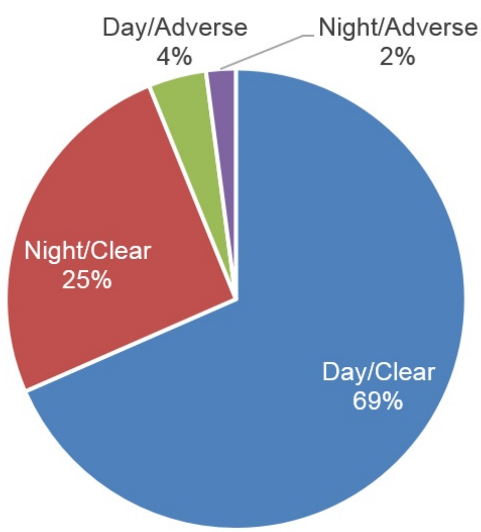

Figure 8: Proportion of highway driving during IVBSS under various environmental conditions.

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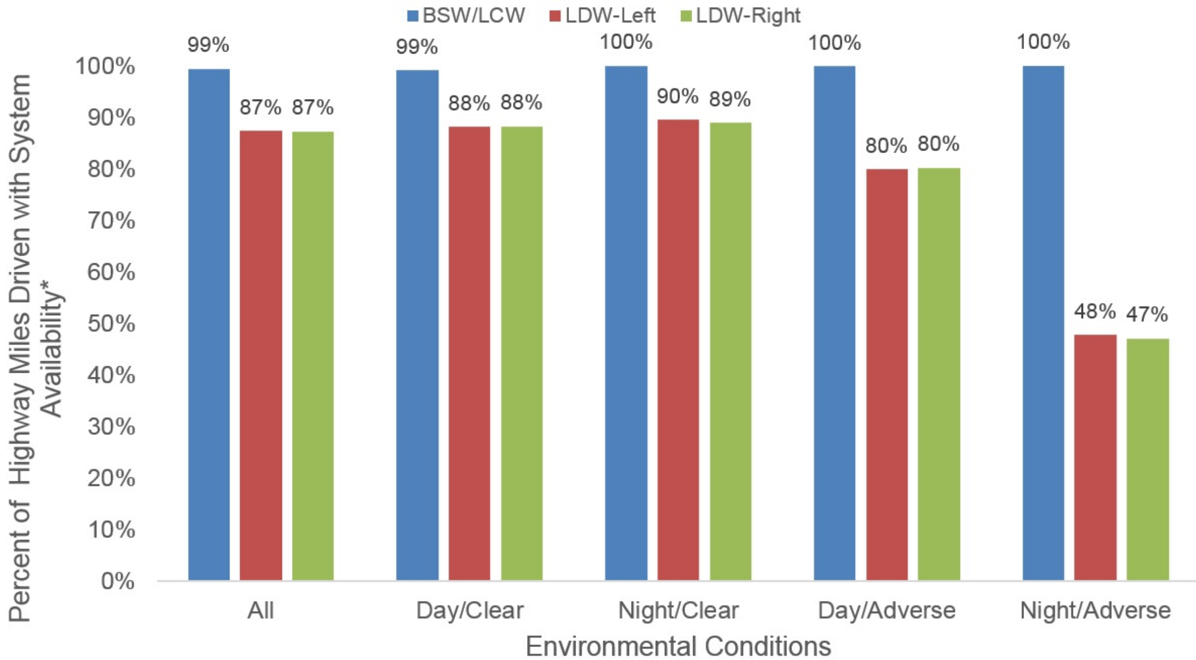
[22] Alerts can be during baseline or treatment condition for FCW, BSW/LCW, or LDW. Near-crash conflicts are determined to be conflicts where minimum safety thresholds were met (e.g., small range between vehicles, small time-to-collision values).

[23] It was noted earlier that the proposed system would be negligibly affected by these environmental conditions. However, instances exist where environmental conditions would significantly impact sensor input (e.g., blocked sensor view from environmental debris, broken sensor from environmental debris, extreme glare, reflection, and/or lighting issues, and environmental debris covering roadways to unrecognizable conditions).

Given that the majority of highway driving occurred during clear weather and the day, the proposed advanced vehicle application should perform well under these conditions. However, when operating under adverse weather or night, the proposed advanced vehicle application should be able to operate with high confidence and accuracy. Figure 9 below shows the confidence and IVBSS system availability for the applications, as percent of miles driven, under various environmental conditions.



*No information on the FCW system availability

Figure 9: System availability (percent of miles driven on highways) under various environmental conditions

It can be seen that under clear weather conditions, the system was operating at over 88 percent for the LDW system. The small percent of miles driven with no availability is most likely due to poor road maintenance and missing lane markings. However, when the weather is adverse, the system availability drops to below 50 percent. This shows that the system relies heavily on the available lane markings and the ability to accurately determine lane and road boundaries. Adverse weather can diminish sensor input by covering lane markings and skewing road boundaries. For an advanced vehicle application operating under these conditions, having low confidence in sensor inputs can trigger major consequences, including erratic behavior and even crashes. The BSW/LCW system was available for almost 100 percent of highway miles. This could be from the fact that the BSW/LCW system did not rely on infrastructure for system availability, rather this application used a side radar and turn signal as the primary inputs. Further analysis is needed to understand the exact conditions and root cause for the system being unavailable or hindered. Results from this analysis will provide input into the possible methodologies to estimate the treatment condition.

Beyond conflicts, alerts give further insight into safety critical events[24]. Figure 10, below, shows the number of valid alerts issued (baseline and treatment) under various conditions. Given that the majority of highway driving is done under clear conditions, the data shows that the highest number of alerts occur during these conditions (this data has not been normalized).

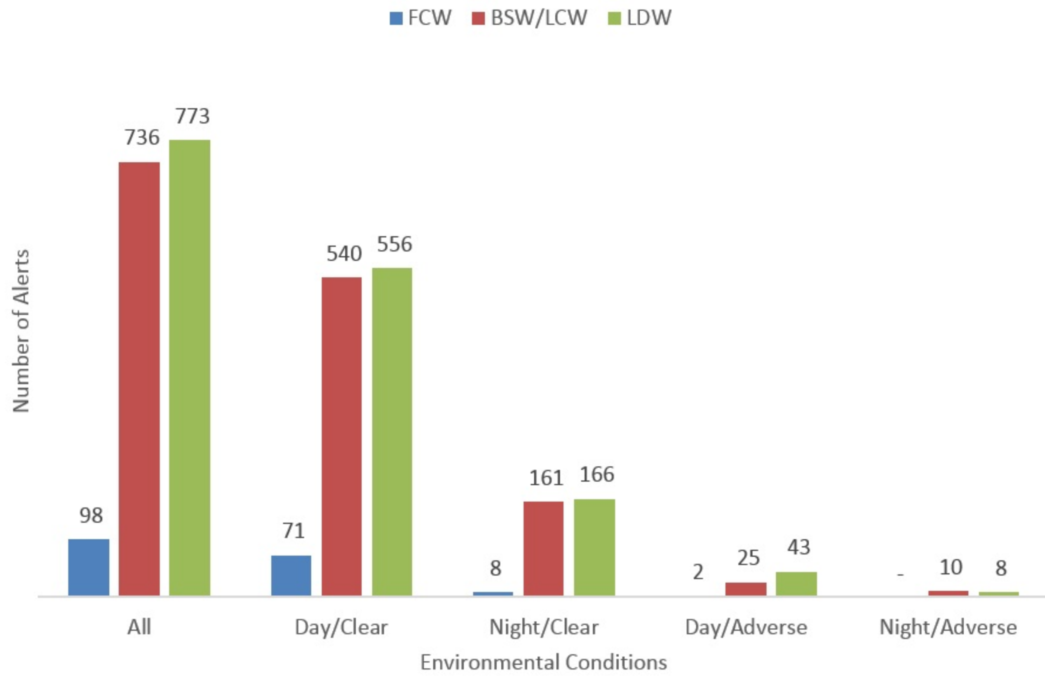


Figure 10: Number of valid alerts for the applications under various environmental conditions

Figure 11 shows similar information for near-crash events. It is of note that the number of alerts and number of near-crash events cannot be directly correlated. The alerts are issued by the system and verified by analysts, while the near-crash events are identified and verified by the analysts (i.e., not all alerts resulted in a near-crash event or not all near-crash events had an alert issued). The numbers presented below for environmental conditions correspond respectively with the environmental conditions described in this section (1) All, (2) Day/Clear, (3) Night/Clear, (4) Day/Adverse, and (5) Night/Adverse.

[24] Conflicts and near-crashes are data mined and post processed using Volpe developed thresholds, while alerts are designed by OEMs and can be issued directly to the driver during the field test. Alerts may be more imminent than conflicts, depending on thresholds set.

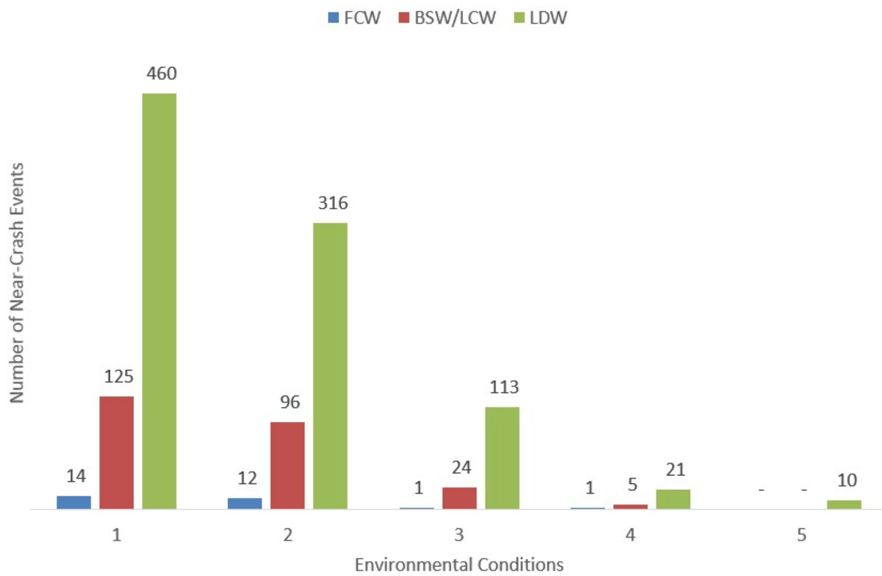


Figure 11: Number of valid near-crash events for the applications under various environmental conditions

These events can characterize specific safety critical events that advanced vehicle applications may encounter within normal driving. By obtaining time history data, these events can by analyzed and assessed for the applicability to advanced vehicle applications and potentially forecast an advanced vehicle application's behavior. Further research and detailed information would be needed to accurately assess the behavior of advanced vehicle applications in similar safety critical events.

3.3.3 Treatment Condition

Given that an advanced vehicle application system is available and can navigate the rigors of normal driving, how an advanced vehicle application handles a safety critical event needs to be further researched. A safety critical event may have been created from other conditions beyond an advanced vehicle application's control (e.g., abnormal traffic pattern, human driver encountering automated vehicle) and potentially exceed the defined ODD. When an advanced vehicle application enters into this conflict, a measure of how the advanced vehicle application handles such an event is required. This measure can be compared to that of a human driver in the same conflict situation. Further research and collaboration are required to accurately quantify an appropriate treatment condition[25].

3.4 Next Steps

Volpe is currently continuing advanced vehicle application research by refining previous research and investigating future data sources and data needs for the benefits estimation methodology. Currently Volpe has two distinct tasks to aid in this research: (1) revising the automated vehicle target crash population and (2)

[25] Collaboration refers to an agreement with an OEM or supplier of an advanced vehicle application that would allow Volpe to learn about the advanced vehicle application, understand the designed ODD, and assess designed system algorithms in order to comprehend and quantify a proper treatment condition.

identifying baseline target conflicts and crashes from available data sources for crash reconstruction simulation with a proposed advanced vehicle application to determine a proper treatment condition.

3.4.1 Revised Automated Vehicle Target Crash Population

As noted earlier, Volpe is estimating preliminary target crash populations for automated vehicles. The target crash populations quantify the addressable historical crash problem size and provide a starting point for identifying a proper baseline condition. This research developed and exercised a methodology to determine target crash populations for concept automated vehicle functions and NHTSA automation levels.

The revised target crash population will use the previous methodology and provide updated statistics. The same mapping system will be used (i.e., five query layers of location, pre-crash scenario, environmental conditions, travel speed, and driver condition) to accommodate the most recent crash data (i.e., 2015 crash calendar year). Further, the revised research will incorporate the SAE Automation Level definitions (instead of NHTSA Automation Levels). Target crash populations will again be presented at the automation level, but will not consist of aggregate concept automated vehicle functions, but focus on the definition of the level and the roles and responsibilities of the driver and system as defined within the SAE automation level definitions.

Currently, the project is scheduled for completion at the end of the 2018 calendar year with a final deliverable of a NHTSA published report, detailing methodology and results.

3.4.2 Baseline Crashes and Conflicts for Crash Reconstructions

Significant effort is needed to develop an accurate baseline state of crashes and conflicts. In early 2017, the Volpe Center kicked off a collaborative effort with an auto-maker who is planning a significant automated driving field test. Tasks in this effort include(1) development of baseline crash and near-crash time-history data set, (2) development of automated vehicle treatment data set based on baseline data, (3) scaling up effectiveness and benefits to national scales (US and/or European), and (4) discussions on the future implications automated vehicles will have on passive safety features. Task 1 is now underway.

The collaborative effort is set to end in 2019, with the goal being that data can be shared and combined to existing data sets for further validation and improved sample sizes, ideas and methodologies can be exchanged to bridge gaps between public and private industries, and collaborative research results can be published and shared, providing future interest in research collaborations amongst public and private industry.

Chapter 4 Vehicle Operations

After completing a market analysis of traffic microsimulation programs, the Volpe research team utilized PTV Vissim (“PTV Vissim,” n.d.). Vissim was chosen due to its ability to easily alter the parameters of the car following model, including the oscillation behavior of the vehicle, an aspect critical for automated vehicle modeling. Vissim’s internal car following behavior is based on the Wiedemann 99 Psycho-Physical Model which assumes that when following another vehicle, a driver’s longitudinal behavior is based on which “reaction zone” the driver is in. Figure 12 depicts the Wiedemann approach including a description of each of the “thresholds” in the model. Parameters and thresholds in the car following model include:

- Look-ahead distance
- Look back distance
- Duration and probability of not paying attention
- CC0 – Standstill distance (ft)
- CC1 – Headway time (s)
- CC2 – Following variation (ft)
- CC3 – Threshold for entering ‘Following’
- CC4 – Negative Following Threshold
- CC5 – Positive Following Threshold
- CC6 -- Speed dependency of Oscillation
- CC7 -- Oscillation Acceleration (ft / s^2)
- CC8 -- Standstill Acceleration (ft / s^2)
- CC9 -- Acceleration with 50 mph (ft/s^2)

To calibrate the model, one can change the inputs that govern the oscillation behavior. Furthermore, it was confirmed, with technical staff at Vissim, that by changing the Wiedemann 99 oscillation parameters (CC2, CC4, CC5, CC6, and CC7) to zero, one could approximate the car following behavior of an automated ACC vehicle; as an automated vehicle will not have unconscious (or subconscious) reactions.

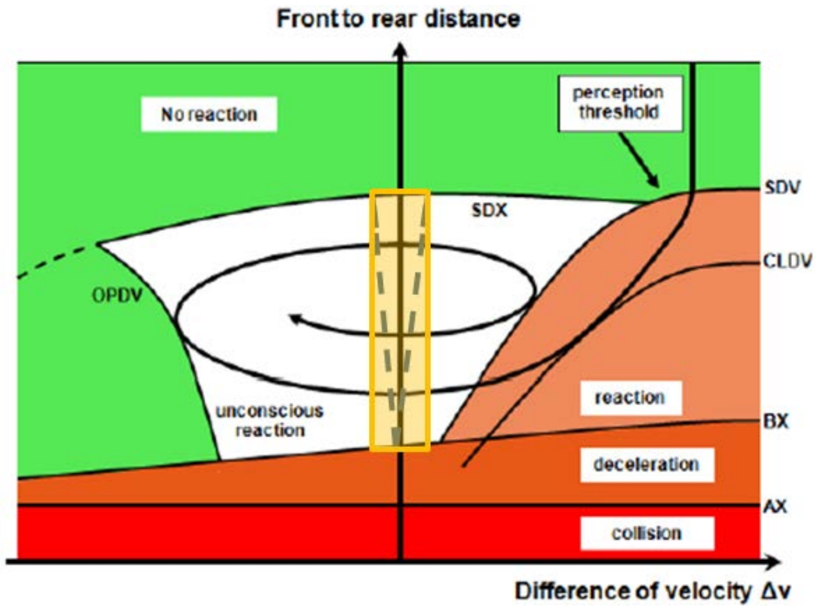


Figure 12: Wiedemann car following model (Fellendorf, 2001)

In addition to simulating an ACC vehicle using an adaptation of the Wiedemann model, Vissim also provides the capability to input an alternate program to govern the vehicle behavior, through a dynamic link library (.dll). This is advantageous because numerous equations have been developed that govern, and/or simulate, the car following behavior of an ACC system. Two notable models are the Microscopic model for Simulation of Intelligent Cruise Control (MIXIC)[26] and Intelligent Driver Model (IDM)[27]. We utilized these models because they (1) reduced our requirement to develop the program code for these models, and (2) provided us the ability to perform a true test of our Framework.

4.1 Analyzing Mobility in the Framework

As discussed in (Smith et al., 2015) the intention of the Framework is to provide an analytical approach that could allow researchers and government agencies to directly compare the potential benefits of different technologies to one another. The schematic below describes the approach that we have taken to develop the vehicle operations (may be used interchangeably with mobility throughout this document) portion of the Framework. Our approach has been:

1. Initially develop and test a simple road network, but over time migrate to a more realistic one.
2. Test a variety of automation technologies and potential applications. To date we have tested the modified Wiedemann 99 car-following model with the oscillation size set to 0, IDM, and MIXIC, the latter being used to model Cooperative Adaptive Cruise Control (CACC)
3. Prepare the data for environmental analysis modelling in the Motor Vehicle Emission Simulator (EPA, 2014). We have defined the steps required, and are now validating to determine the limits of the feasible network.

[26] (Van Arem, de Vos, & Vanderschuren, 1997)
[27] (Kesting & Treiber, 2008)

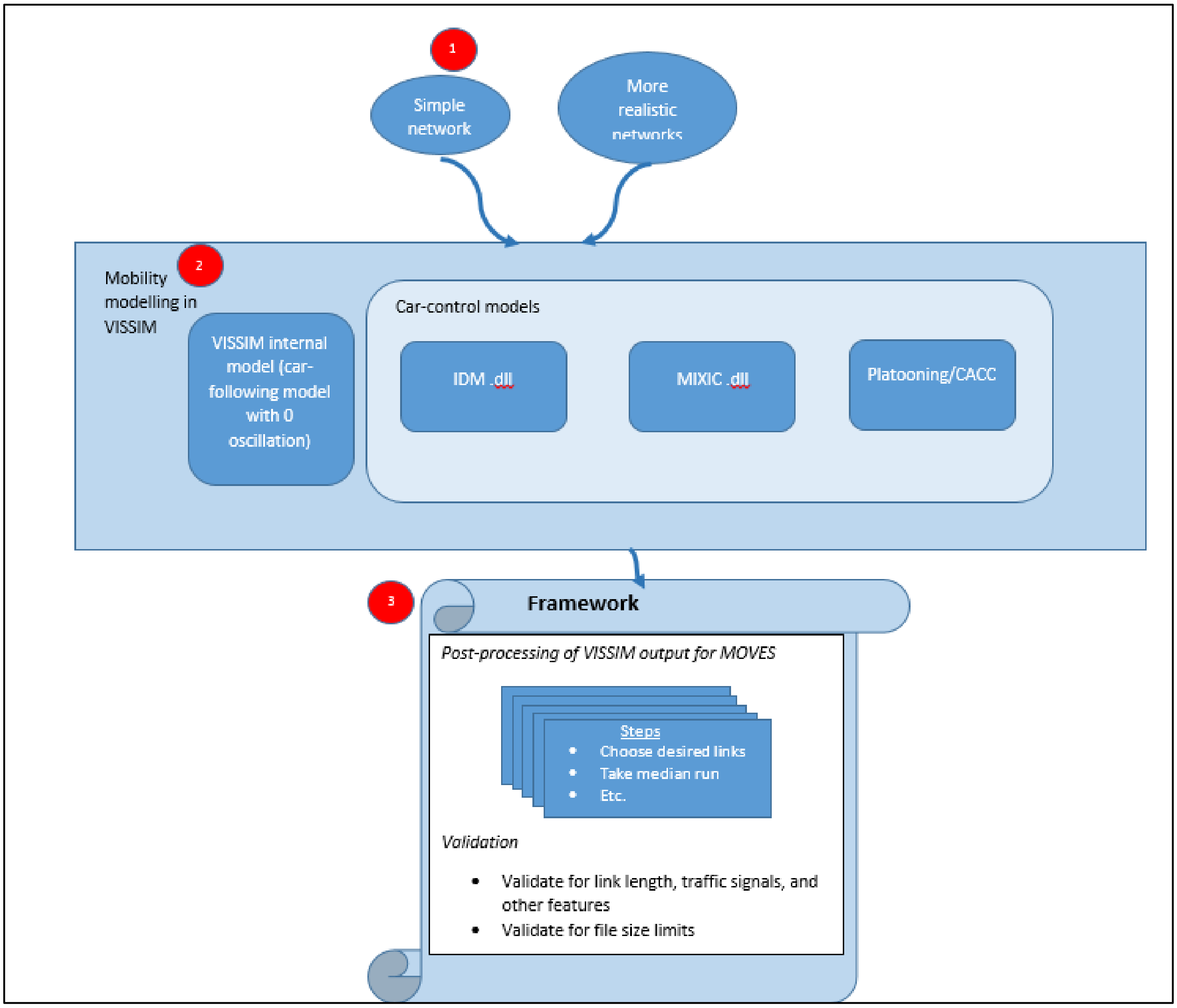


Figure 13: Framework for modeling vehicle operations

4.2 Initial Findings on an Idealized Road

A number of previous research studies have analyzed the potential mobility benefits of ACC, and the findings are mixed. While the majority of papers report some benefits of ACC vehicles, there are a few that suggest the large headway gaps will lead to cut-ins/lane changes which will reduce overall traffic flow, and that string instability will create traffic shockwaves. Furthermore, among the researchers that report benefits for ACC vehicles, there is variability in the size of the benefits (e.g., reduced congestion, reduced pollution, higher throughput). This variability reinforces the need for a standardized benefits estimation framework.

To date we have modeled 4 different scenarios:

- No ACC: This is the baseline for analysis. The driver behavior is governed using the Wiedemann 99 car following approach using the default values of the model.

- Wiedemann ACC: As described above, this is the default car following model but the driver oscillation was been removed.
- The MIXIC Driver Model
- The Intelligent Driver Model

This initial work focused on 100% vehicle penetration. In the Vissim model runs, a two-lane freeway, approximately 3 miles long, is run through a 4,500-second simulation run, performing calculations and collecting data at a 10 Hz rate. The freeway is constructed out of 3 links and 2 connectors, with the middle link being approximately 2 miles long. To ensure that traffic has reached equilibrium, data is only collected on link 2 and only from 900-4,500 seconds (one hour). Vissim was run at a number of different desired vehicles/hr, which allowed us to identify the maximum vehicle capacity for each of the scenarios. The maximum lane capacity for each of the scenarios is shown below.

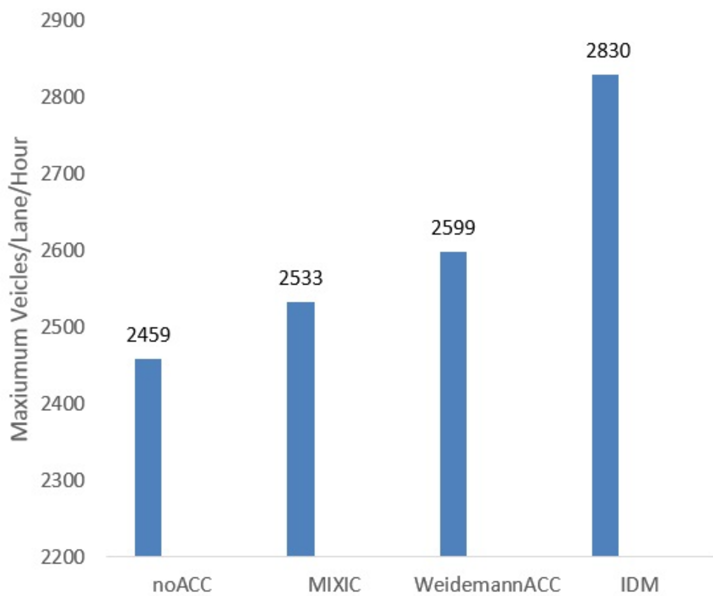


Figure 14: Maximum lane capacities

The majority of the initial findings are consistent with previous studies; ACC technology at 100% market penetration could produce a slight improvement in road capacity. Chapter 5 describes our initial use of CACC modeling, results on a real freeway segment, and the linkage to the EPA MOVES model for energy and emissions analysis.

4.3 Case Study on a Real-World Network

To test the Automated Vehicle Benefits Modeling Framework on a real-world road network, we selected Interstate 91 northbound (NB) near Springfield, Massachusetts. The following case study simulating vehicle trajectories on I-91 NB is drawn from our paper that is currently under review (Eilbert, Noel, Jackson, Sherriff, & Smith, 2018).

This I-91 NB network is a freeway segment with five on-ramps and seven off-ramps over roughly three miles and consisting of mostly three lanes. Much of the energy and emissions analysis below focuses on the I-91 freeway links between Route 5 and Interstate 291 since they present optimal conditions for simulating cars with CACC systems. A visualization of the I-91 NB network near Springfield is provided as Figure 15 below with the I-91 links labeled 100-104 and observed weekday morning traffic volumes at nodes 1-5.

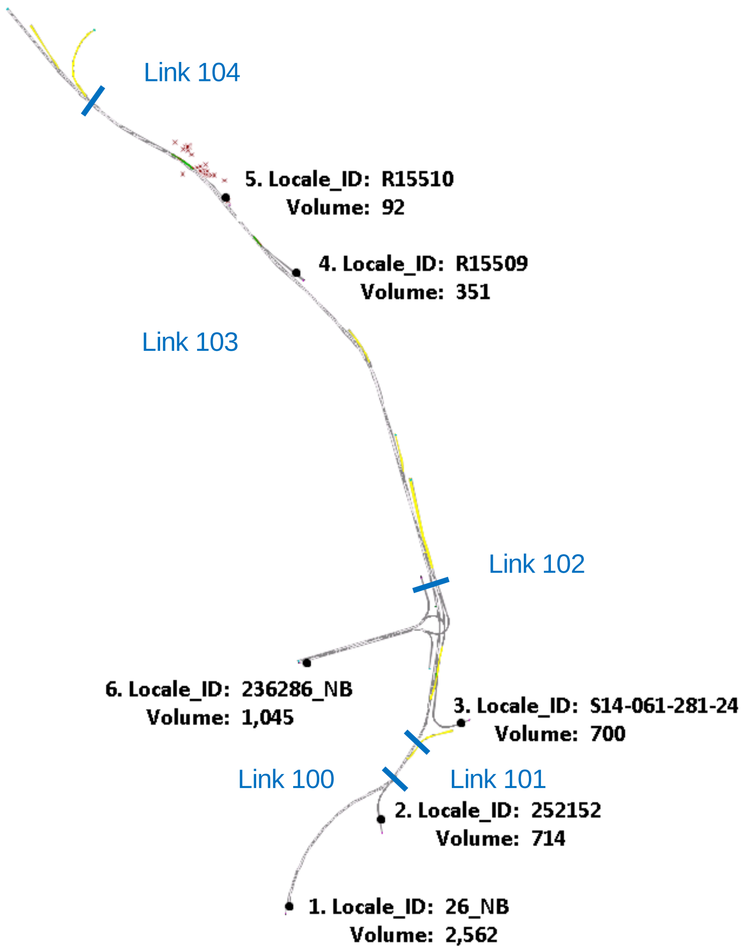


Figure 15: I-91 Vissim network implementation with observed weekday morning traffic volumes entering the network and labeled links 100 through 101.

4.3.1 Network Calibration

Traffic volumes on the I-91 NB network were defined in the microsimulation using traffic counts from the Massachusetts Department of Transportation (MassDOT) Transportation Data Management System ("Traffic Volume Counts - MassDOT Highway," n.d.). We used the most recent counts from weekday mornings from 07:00 to 08:00. Utilizing these MassDOT records, the volumes were specified in Vissim from the corresponding field sensor locations presented in the figure above. The MassDOT volume data indicates that more than 2,500 vehicles entered the network from I-91 (Node 1) and that about 1,000 vehicles entered from the west on Route 5 (Node 6) and about 700 vehicles entered from the east on Route 5 (Node 2). Volumes entering from Massachusetts-83 (Node 3) were not available and were therefore estimated from other nearby ramps to be 700 vehicles. On-ramps from local roads had roughly 350 vehicles (Node 4) and 90 vehicles (Node 5) entering the network, respectively.

A cumulative speed distribution was developed for the I-91 network from a nearby speed sensor (I-91 northbound from Route 5 southbound, MassDOT Data Locale ID 2797). The desired I-91 speed measurements were collected in April 2017 in the following speed bins: 0-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, and 85-119 mph. For simplicity, the first and last speed bins were dropped and then cumulative percentages were calculated for each speed bin in the truncated dataset and assigned to the midpoint speed of the bin. Figure 16 below shows the midpoint speed-cumulative percentage pairs plotted for the I-91 network with a normal cumulative distribution of speeds for reference. The measured I-91 speed distribution was then used as an input to the traffic microsimulations across the three scenarios and all 45 test runs.

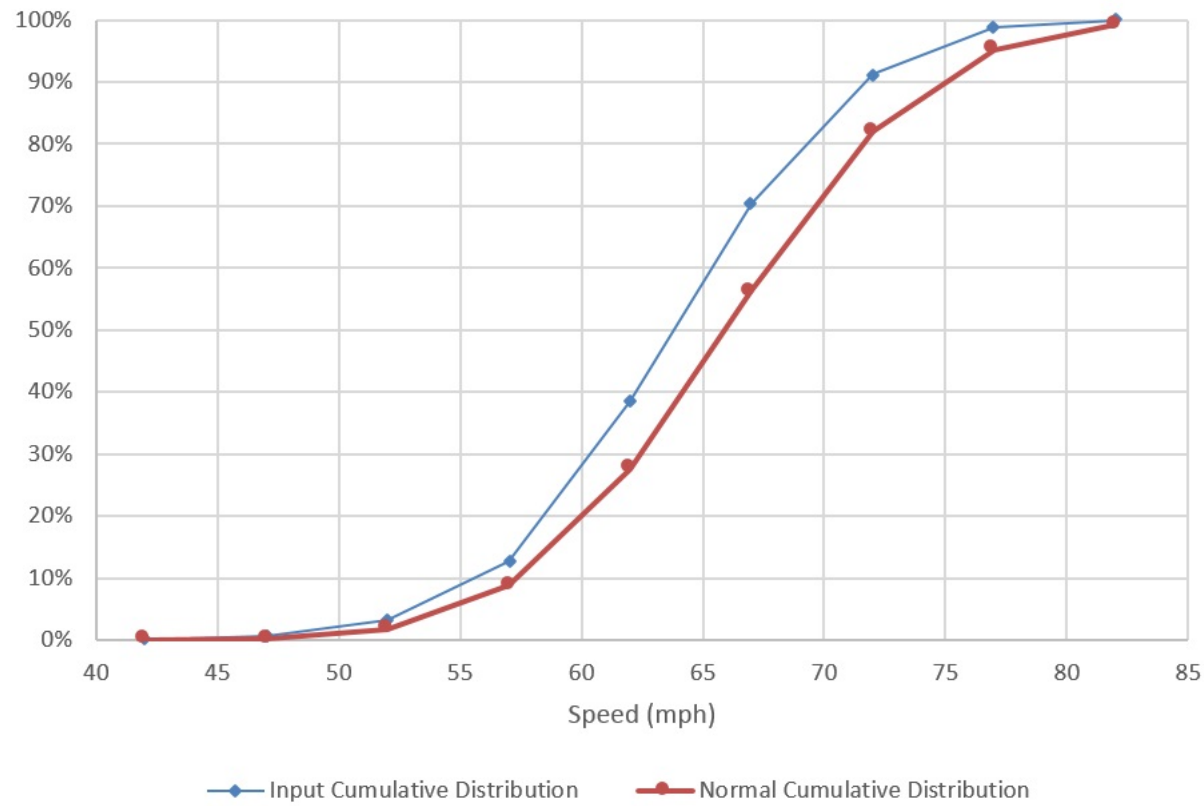


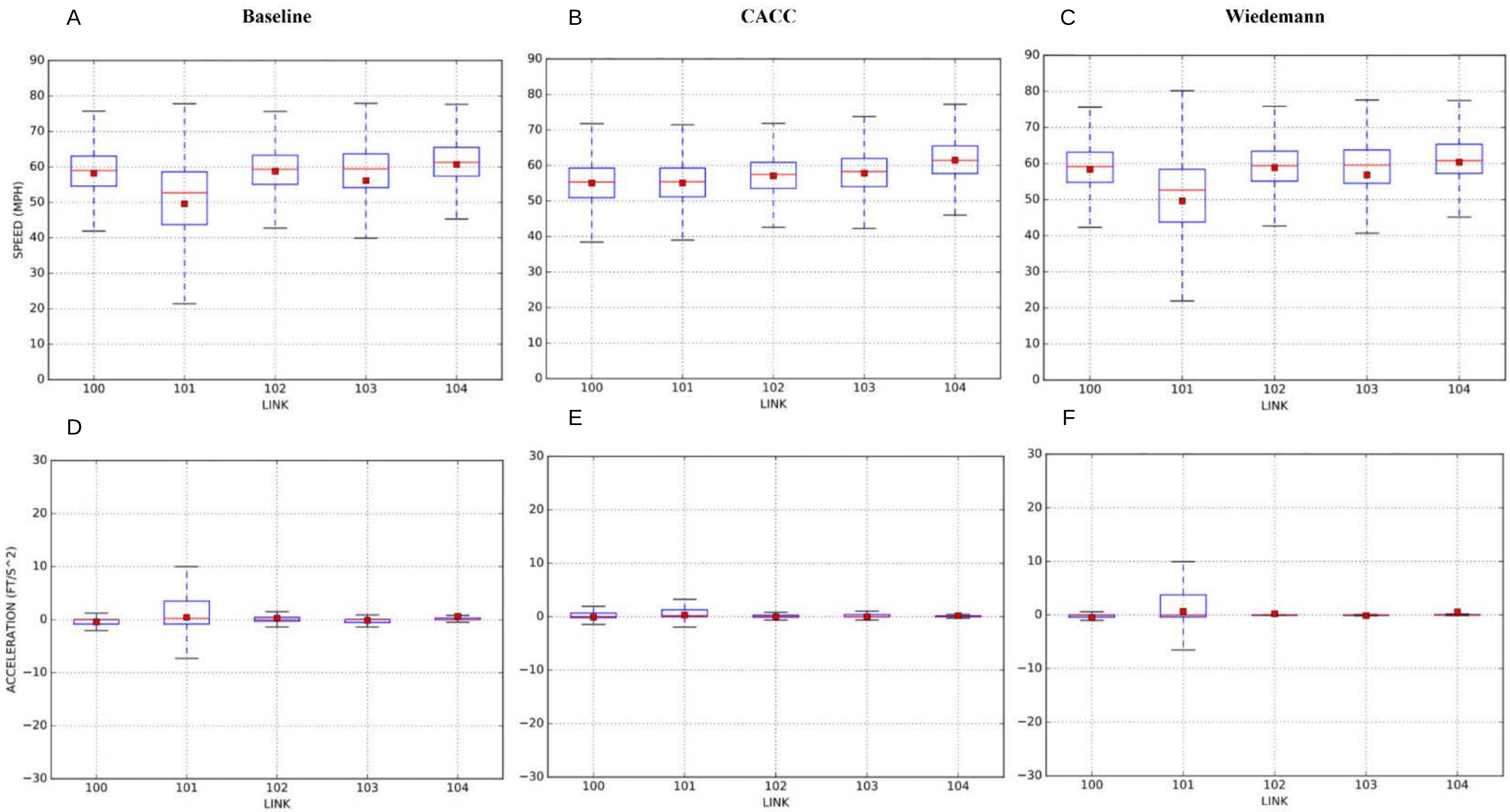
Figure 16: Cumulative speed distribution derived from I-91 speed measurements and a normal cumulative distribution for reference.

Summaries of vehicle speed, acceleration, delay time, and headway results from the first random seed of traffic microsimulations for the I-91 northbound network are presented as box plots below in Figure 17. Interestingly, we found that the second scenario with CACC driving does not increase average vehicle speeds over the baseline scenario except for Link 101, but it does narrow the range of speeds, particularly for links with higher levels of congestion, as shown in Figure 17a. The third scenario where the Wiedemann 99 oscillation parameters have been set zero does not show appreciable difference in speeds from the baseline. In Figure 17b, CACC driving appears to smooth accelerations across all links besides Link 100 while setting the Wiedemann oscillations to zero generated even more constant speeds with the exception of Link 101. This may suggest that the Wiedemann 99 car following model with no oscillations does perform well on congested links.

Additional analysis show CACC driving leads to some small to moderate reductions in delay time over the baseline, especially for Link 101 and 104, but increases delay time slightly for Link 100, possibly due to the merging with Route 5 ahead in the next link. The Wiedemann scenario without oscillations offers marginal improvements to baseline delay time if at all, only Link 104 shows a modest improvement.

Headway has mixed results in Figure 17d. CACC driving yields an observable reduction in maximum headway for Link 100, 102, and 103 but not for Link 101 nor 104, potentially due to the MIXIC model leaving more following distance than Wiedemann 99 for merging situations. The CACC and baseline scenarios did not show any perceptible difference in mean and median headways. The Wiedemann scenario has little effect on headway and even produces small increases in maximum headway for the first three links.

Figure 17: Box plots of vehicle speed (mph) and acceleration (ft/s^2) for the first random seed on the I-91 network by link and scenario (red dot represents the mean).



4.4 Vehicle Operations Modeling Limitations

The current AV Benefits Framework relies in part upon microsimulation modeling techniques. While microsimulation is a powerful tool, it is necessary to recognize the limitations of solely relying on its results to identify the potential mobility benefits of AV technologies.

Our current microsimulation approach will allow us to evaluate the benefits related to:

- Reduction in following distances/improvements in reaction time
- The potential to eliminate the negative impacts of vehicle longitudinal oscillation
- Platooning and managed lane changes

Microsimulation analysis does not readily identify benefits (or dis-benefits) related to:

- Gawker/rubbernecking delay for both accidents and police action [Modeling of mobility impacts of crashes, as lane/road closures of varying durations]
- Lane closure for accidents and work zones[28]
- Reduced field of vision resulting from
    - solar glare
    - curved roadway where barriers limit sight
    - reduced sight at the crest of a hill.

Finally, we recognize the need to be cautious of benefits identified through microsimulation analysis. Significant calibration of model variables is required to recreate traffic observations of any road/area of interest. Even then, the model is only recreating what was observed on a particular time and date, and is easily invalidated by changing any travel conditions. As driver behavior (of the remaining manually-driven vehicles) changes due to the introduction of automation, simulation models will need to be recalibrated.

The next phase of CAV modeling will include scenarios with higher congestion and mixed traffic with varying penetration rates of CACC-enabled vehicles. In the future, we may explore other driving behavior models for CACC, utilize different road networks, and/or consider modeling additional automation technologies like speed harmonization or platooning.

[28] The Volpe Center and Turner Fairbank currently have a separate project underway to model driver behavior in work zones.

Chapter 5 Energy / Emissions

To assess energy consumption and tailpipe emissions, we link a traffic microsimulation model to a modal emissions model, utilizing a second-by-second drive schedule output characterizing driving behavior from the mobility analysis as a key input into MOVES2014a to estimate fuel efficiency and emission reductions. MOVES2014a was chosen because of its availability as a regulatory tool as well as its robust methodology. This chapter includes direct excerpts from our previous publications on the potential energy and emission benefits of connected and automated vehicle technology.

As we discuss in our first publication on energy and emission modeling (Reed, Noel, Smith, Rakoff, & Bransfield, 2015), MOVES2014a operates by calculating emission rates based on a variety of inputs, including vehicle type, age, fuel, speed, acceleration, vehicle miles traveled, acceleration, idling times, number of cold starts, soak times, meteorological data, and road-link characteristics. For running emissions, rates are estimated through assignment into operating modes. For light-duty vehicles, a key indicator of operating mode assignment is through the calculation of the vehicle specific power (VSP), or tractive power exerted by the vehicle normalized by the vehicle's weight. Given a second-by-second drive schedule, VSP at time *t* can be calculated using the following equation:

$$VSP_t = \frac{Av_t + Bv_t^2 + Cv_t^3 + mv_t a_t}{m}$$

In which,
A = tire rolling resistance term (KW sec/m)
B = rotational resistance term (KW sec/m^2)
C = aerodynamic drag term (KW sec/m^3)
v_t = velocity at time, t (m/s)
a_t = acceleration at time, t (m/s^2)
m = mass (kg)

Once the VSP_t is calculated, an operating mode can be assigned taking into account defined bins for operating speed and acceleration. Operating modes are shown in the table below:

Table 6: Description of assignment of operating mode for MOVES analysis

Operating Mode	Operation Mode Description	Vehicle-Specific Power (VSP_t, kW/metric ton)	Vehicle Speed (v_t, mph)	Vehicle Acceleration (a_t, mph/sec)
0	Deceleration/Braking	n/a	n/a	$a_t \le -2.0$ OR ($a_t < -1.0$ AND $a_{t-1} < -1.0$ AND $a_{t-2} < -1.0$)
1	Idle	n/a	$-1.0 \le v_t < 1.0$	n/a
11	Coast	$VSP_t < 0$	$1 \le v_t < 25$	n/a
12	Cruise/Acceleration	$0 \le VSP_t < 3$	$1 \le v_t < 25$	n/a
13	Cruise/Acceleration	$3 \le VSP_t < 6$	$1 \le v_t < 25$	n/a
14	Cruise/Acceleration	$6 \le VSP_t < 9$	$1 \le v_t < 25$	n/a

15	Cruise/Acceleration	$9 \le VSP_t < 12$	$1 \le v_t < 25$	n/a
16	Cruise/Acceleration	$12 \le VSP_t$	$1 \le v_t < 25$	n/a
21	Coast	$VSP_t < 0$	$25 \le v_t < 50$	n/a
22	Cruise/Acceleration	$0 \le VSP_t < 3$	$25 \le v_t < 50$	n/a
23	Cruise/Acceleration	$3 \le VSP_t < 6$	$25 \le v_t < 50$	n/a
24	Cruise/Acceleration	$6 \le VSP_t < 9$	$25 \le v_t < 50$	n/a
25	Cruise/Acceleration	$9 \le VSP_t < 12$	$25 \le v_t < 50$	n/a
27	Cruise/Acceleration	$12 \le VSP_t < 18$	$25 \le v_t < 50$	n/a
28	Cruise/Acceleration	$18 \le VSP_t < 24$	$25 \le v_t < 50$	n/a
29	Cruise/Acceleration	$24 \le VSP_t < 30$	$25 \le v_t < 50$	n/a
30	Cruise/Acceleration	$30 \le VSP_t$	$25 \le v_t < 50$	n/a
33	Cruise/Acceleration	$VSP_t < 6$	$50 \le {}_vt$	n/a
35	Cruise/Acceleration	$6 \le VSP_t < 12$	$50 \le v_t$	n/a
37	Cruise/Acceleration	$12 \le VSP_t < 18$	$50 \le v_t$	n/a
38	Cruise/Acceleration	$18 \le VSP_t < 24$	$50 \le v_t$	n/a
39	Cruise/Acceleration	$24 \le VSP_t < 30$	$50 \le {}_vt$	n/a
40	Cruise/Acceleration	$30 \le VSP_t$	$50 \le v_t$	n/a

In order to run MOVES, vehicle type, meteorology, fuel specifications, and road network data must be input. Road network data consists of link length, link grade, traffic volume and composition, and link speed (Alam, Ghafghazi, & Hatzopoulou, 2014). Link speed can be supplied through three methods: average speed distribution, second-by-second link drive schedules, or operating mode distributions. In this study, we are utilizing operating mode distributions input by externally calculating VSP and assigning operating mode using an external tool developed in Python. Studies have shown that when users input either operating mode distribution or second-by-second driving schedules, MOVES gives better estimates of emissions than with the average speed distribution (Alam et al., 2014) (Abou-Senna & Radwan, 2014) (Yao, Wei, Perugu, & Liu, 2014). Emission rates are estimated given the vehicle characteristics as well as road and meteorological conditions.

There are numerous challenges associated with the environmental analysis, categorized broadly as challenges associated with the MOVES model and challenges associated with the entire Framework.

The MOVES2014a model, while a powerful tool for estimating emissions and fuel consumption, relies on some limiting assumptions. For one, the terms in the vehicle-specific power calculation, a key parameter in estimating emissions rates, are based upon averages meant to represent all vehicles in a given vehicle class. In reality, there can be significant variation in the performance of vehicles within a vehicle class, resulting in an inherent uncertainty within the model that has not been well characterized. Given that there are multiple variables within this complex model, impacts from a given automation scenario can have substantial uncertainty. Therefore, it may only be possible to report qualitative results (e.g., some benefit, or no substantial benefit) in many cases. Additionally, using MOVES2014a as a means of assessing environmental impacts may potentially miss some benefits. For instance, land use does not directly affect emissions or fuel consumption but certain land users (carbon sinks) can benefit air quality and offset emissions production. Also, MOVES2014a uses a tractive power calculation rather than an engine power calculation and so could miss the nuances associated with gear shifting, steering, or pedal control (Fontaras et al., 2015).

Challenges also lie in properly modeling the safety, mobility, travel behavior, and personal mobility components of the project. Earlier modeling and analysis in these areas necessarily changes the inputs to the environmental analysis and should be properly understood to track impacts. Using default values for car-following and other applications found in a microsimulation traffic model, for instance, may not properly reflect real car-following behavior, resulting in a skewed estimation of emissions and fuel consumption. It is difficult but important to have a foundational understanding of the assumptions upstream of the environmental analysis in order to report trends and impacts.

5.1 MOVES2014a Setup

Using MOVES 2014a to calculate emissions and fuel consumption, the following shows the inputs used to set up the MOVES run.

- Description
  - <blank>
- Scale
  - Model: On road
  - Domain/Scale: Project
  - Calculation Type: Inventory
  - Years: 2020
  - Months: January
  - Days: Weekdays
  - Hours: 00:00-00:59
- Geographic Bounds
  - Region: Custom Domain
  - StateID: 99
  - County ID: 1
  - GPA Fraction: 0.0
  - Bar. Pressure: 28.94
  - Vapor Adjust: 0
  - Spill Adjust: 0
- Vehicles/Equipment
  - Fuels: Diesel, Electricity, Ethanol (E-85), Gasoline
  - Source Use Type: Passenger Car
- Road Type
  - Selected Road Type: Rural Restricted Access
- Pollutants and Processes (selected)
  - Total Gaseous Hydrocarbons: Running Exhaust and Crankcase Running Exhaust
  - Non-methane Hydrocarbons: Running Exhaust and Crankcase Running Exhaust
  - Volatile Organic Compounds: Running Exhaust and Crankcase Running Exhaust
  - Carbon Monoxide (CO): Running Exhaust and Crankcase Running Exhaust
  - Oxides of Nitrogen (NOx): Running Exhaust and Crankcase Running Exhaust
  - Primary Exhaust PM2.5 – Total: Running Exhaust and Crankcase Running Exhaust
  - Primary PM2.5 – Brakewear Particulate: Brakeware
  - Primary PM2.5 – Tireware Particulate: Tirewear

- Manage Input Data Series
  - <blank>
- Strategies
  - Rate of Progress: <blank>
- General Output
  - Units: Mass – Grams, Energy – Million BTU, Distance – Miles
  - Activity: Distance Traveled, Source Hours
- Output Emission Detail
  - On and Off Road: <None Selected>
  - For All Vehicle/Equipment Categories: Fuel Type
- Advanced Performance Features
    - <blank>

Within the Project Data Manager, data input for the project-level is described below in Table 8. Many of the data used in the project-level run were obtained by running a national-scale inventory run and then applying national rates and values.

Table 7: Project data sources

Data	Source
Age Distribution	MOVES2014a Default Age Distribution Tool for 2020
AVFT	National-scale inventory run
Fuel Formulation	National-scale inventory run
Fuel Supply	National-scale inventory run
Fuel Usage Fraction	National-scale inventory run
Generic	---
Hoteling	---
Inspection & Maintenance (I/M) Programs	No I/M programs
Links	Vissim microsimulation model setup and output
Link Source Type	Source type: 21, Source type hour fraction: 1
Meteorological Data	National-scale inventory run
Off-Network	---
Operating Mode Distribution	Python-derived data from Vissim vehicle trajectory output
Retrofit Data	---
Tools	---
Zone	all allocation factors set to: 1
Zone Road Type	Road Type: 2, Source hours factor set to: 1

5.2 Operating Modes and Vehicle Trajectory Data Processing

Another way to examine the link-level performance is through operating mode distributions, as shown in Figure 4. Operating modes are necessary for utilizing MOVES because MOVES computes tailpipe exhaust emissions and energy consumption using time-dependent emissions and fuel measurements by operating mode. For each link-specific operating mode distribution in the I-91 Springfield network, the first random seed is represented by the bar plot and other 14 seeds are represented by the scatterplot to highlight the variability between simulations. As one might expect, most of the time on these highway links is spent driving at speeds above 50 mph (operating modes 33-40) and in midrange VSP bins or braking (operating mode 0).

As an example, we present a plot of the operating mode distribution of Link 101 from the I-91 network in Figure 18 below, where we express the variability in the microsimulations by displaying the first random seed as a bar and the other seeds as dots. We find that braking (operating mode 0) and driving in operating mode 30 at moderate speed (25-50 mph) and high power (30+ kW per metric ton) drop drastically from the baseline to the CACC scenario. While the Wiedemann scenario without any oscillations did reduce time in some higher operating modes compared to the baseline, it showed increases in operating modes 30 and 40, which have the highest VSP bins.

To expedite the energy and emission estimates, the external Python tool also automatically created a MOVES project-scale input database for the *link*, *linksourcetypehour*, and *opmodedistribution* tables. The *link* table contains link-specific road type, length, traffic volume, and average speed and the *linksourcetypehour* table indicates the hourly allocation of vehicle source use type, which was network-specific but did not vary by link or simulation. None of the other project-scale inputs were changed for our energy and emissions analysis.

For each of the 45 microsimulations, the standard MOVES run specifications (stored in an .mrs XML file) were edited to include the appropriate input database. Each modified .mrs file was then placed in a MS-DOS batch file and run from the command line rather than the MOVES graphical user interface, which can be tedious to repeatedly run. The external Python tool processed the 17.5 gigabytes of 10 Hz Vissim-generated vehicle trajectories through MOVES project-scale analysis with a single button click.

5.3 Scenario Development and Results

Our research focuses on the potential energy and emission benefits of connected and automated vehicle (CAV) technologies like cooperative adaptive cruise control. To date we have developed three distinct studies to evaluate energy and emission impacts from CAV technologies:

1. The first publication (Reed et al., 2015) examines a scenario on an idealized highway network through traffic microsimulations of passenger cars with the oscillation parameters of the Wiedemann 99 car following model set to zero, as discussed in the chapter on vehicle operations, which has been tested in previous literature as a rough representation of low level of vehicle automation.
2. The second publication plugs in a CACC driving behavior model supplied by DOT's Turner-Fairbank Highway Research Center into the microsimulations on the idealized network and starts to experiment with different traffic volumes and market penetrations of CACC (Eilbert, Noel, Bransfield, O'Donnell, & Smith, 2016).
3. The third and most recent publication models the energy and emission impacts of the Wiedemann scenario without oscillations and CACC scenario on a real-world network, Interstate 91 northbound near Springfield, Massachusetts. It goes on to more explicitly describe a three-layered modeling framework that integrates a CAV driving behavior model, a microscopic traffic simulation model, and the US Environmental Protection Agency's MOVES for evaluating the energy and emission impacts of CAV technologies (Eilbert, Noel, Jackson, Sherriff, & Smith, 2018).

In the following sections, we will showcase the energy and emission results from each of these three studies and will highlight the evolution of our modeling efforts.

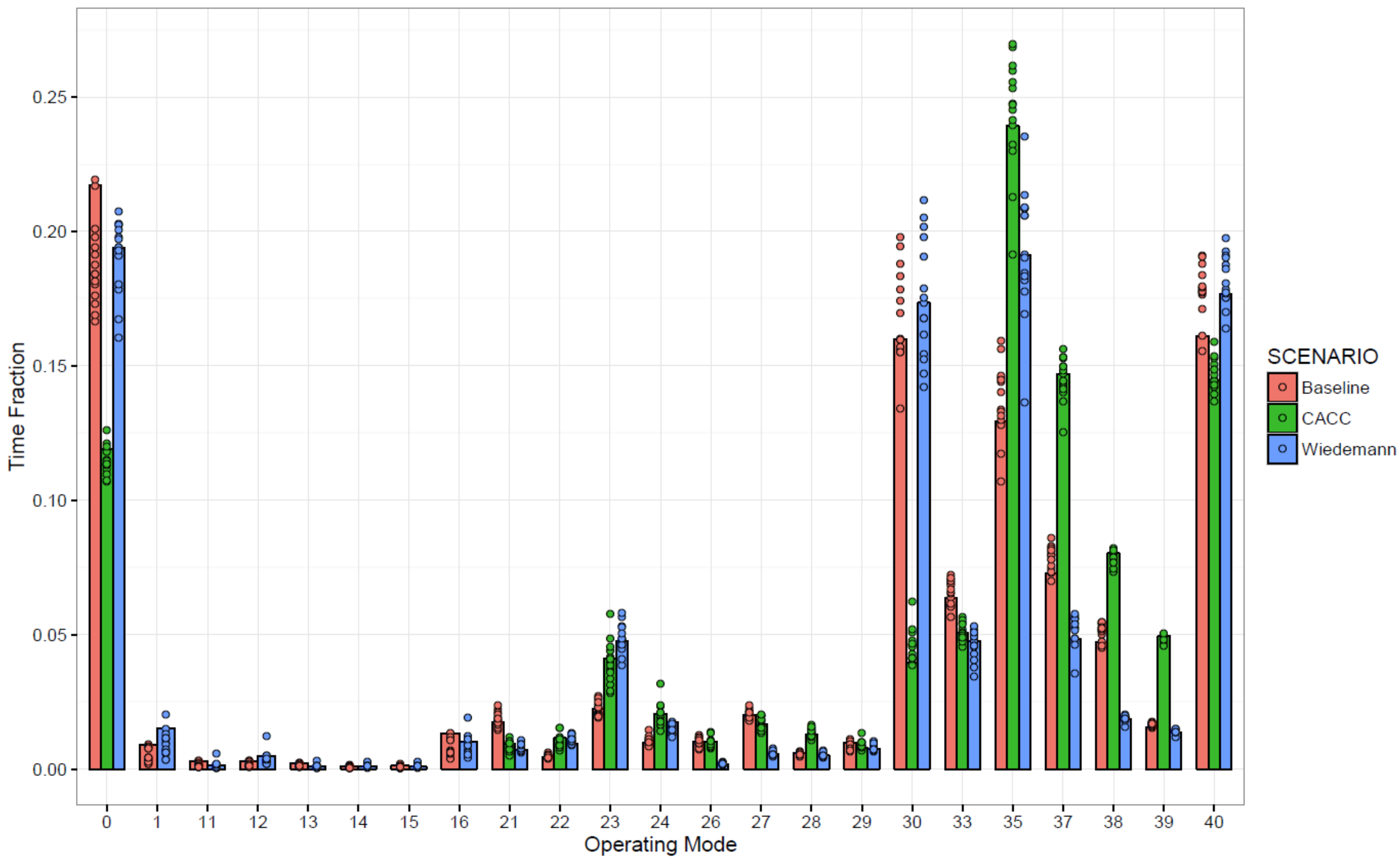


Figure 18: Operating mode distribution of Link 101 on the I-91 network (bar represents the first simulation and the dots represent the other 14 simulations)

5.3.1 Study 1: No Wiedemann 99 Oscillations on an Idealized Network

Using Vissim to model the Wiedemann 99 car following algorithm with oscillation parameters set to zero on an idealized 2-mile highway segment, the MOVES 2014a results for criteria pollutants carbon monoxide (CO), nitrogen oxides (NOx), volatile organic compounds (VOCs), and particulate matter less than 2.5 μm ($PM_{2.5}$) for all four scenarios are shown in Figure 20, below. In this study, there were two scenarios with baseline (human) driving with default Wiedemann 99 car following, one at a low traffic volume and the other at high volume (1,500 and 3,000 vehicles per lane per hour) and two scenarios without Wiedemann 99 oscillations at low and high volume. NOx, VOCs, and $PM_{2.5}$ are also shown in the inset plot to give a better depiction of the emissions produced.

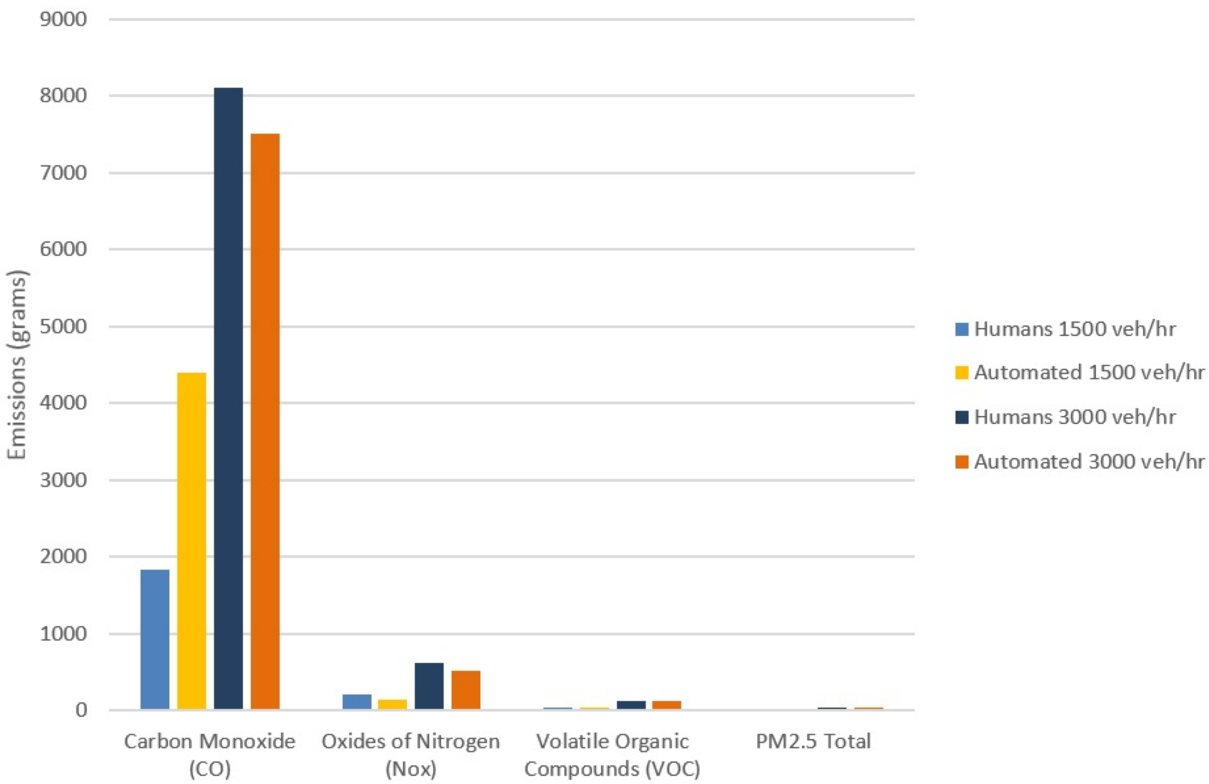


Figure 19: Impacts of Driving Types and Capacities on Emissions

Below is a zoomed in look at the Oxides of Nitrogen, Volatile Organic Compounds, and PM2.5 Total of the above bar chart.

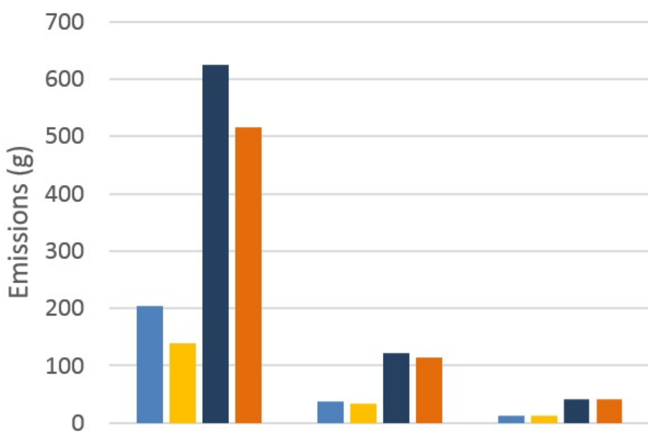


Figure 20: Zoomed in Version of Impacts of Driving Types and Capacities on Emissions

It was found that on average automated vehicles perform the same or better (produce less emissions) than human drivers. The greatest benefit of automated vehicles is in NOx, with a 32% and a 17% improvement over the human driver simulation for the at-capacity and over-capacity conditions, respectively. However, for the largest producing pollutant, carbon monoxide, the human driver simulation at-capacity outperforms the automated vehicles significantly (only producing 1.8 kg of CO compared to 4.4 kg for the automated vehicles). This is expected because of human-driven vehicle operates at higher operating modes than the automated vehicles and carbon monoxide has an inverted relationship to speed. Because carbon monoxide contributes the most (in grams) to overall emissions, for the at-capacity scenario, human drivers produce only half as much emissions as the automated vehicles. For the over-capacity scenario, automated vehicles produce about 7% fewer emissions overall than the human drivers. This shows that automated vehicles can produce a dis-benefit under certain specified conditions, thus validating the importance of developing a robust framework that can fully assess benefits and dis-benefits.

Total fuel consumption for the four modeled scenarios is given below:

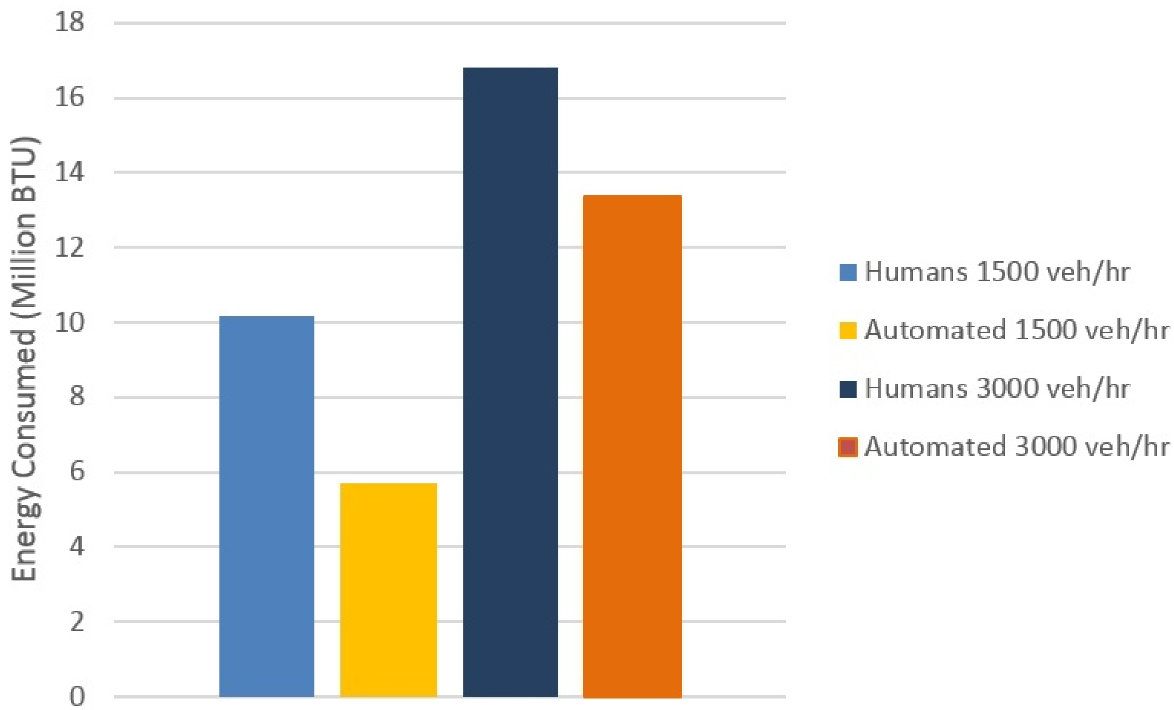


Figure 21: Total fuel consumption for four scenarios on an idealized highway segment

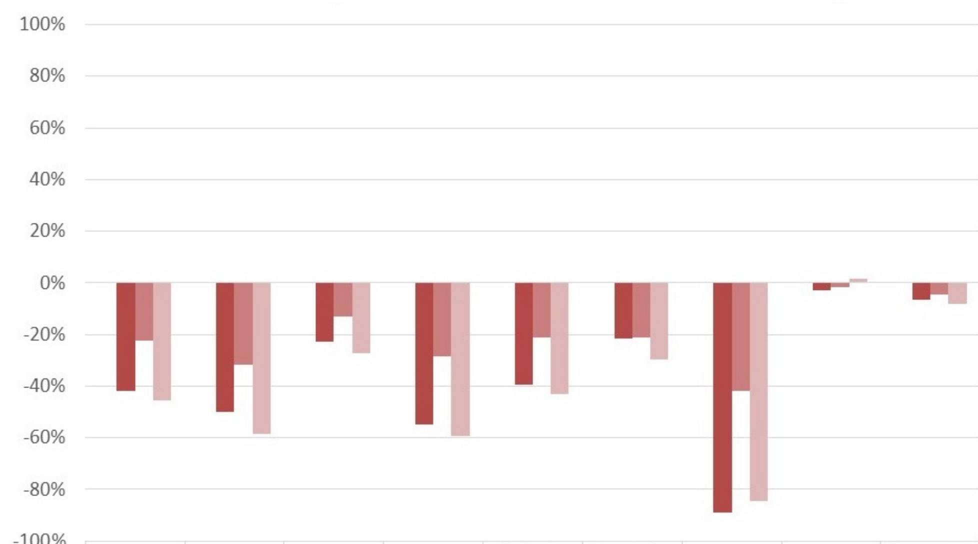
For both roadway conditions, the automated vehicles consumed less energy than the human drivers, with 43% and 20% less fuel consumed in the at-capacity and over-capacity conditions, respectively. Combined with the emissions data, this indicates that there can be a trade-off in assessing benefits from automated vehicles since the scenario with the largest decrease in fuel consumption showed the largest dis-benefit in emissions.

5.3.2 Study 2: Adopted CACC MIXIC Model on an Idealized Network

For the second study, we ran four different scenarios on the same idealized highway segment with the CACC model from Turner-Fairbank discussed earlier:

1. 100% Wiedemann 99 human driving (baseline) at 2400 vehicles/lane/hour
2. 100% driving with coordinated adaptive cruise control (CACC) at 2400 v/l/h
3. 50% CACC & 50% human driving at 2400 v/l/h
4. 100% CACC driving at 4000 v/l/h

The results confirm our initial predictions that vehicles using CACC would produce less emissions than those with drivers. At the same traffic volume, emissions are least for the 100% CACC scenario and are most for the 100% human (baseline) driving scenario. Our findings show that emission rates (g/mi) are less for CACC than human driving when normalized for activity; however, total emissions may not be less. In this study, human driving shows more braking and changes in speed and VSP than CACC causing additional emissions. Our results showed a high percentage of CACC driving falls into operating mode 35 with speeds greater than 50 mph and moderate VSP, as shown in the figure below.



	Total Hydrocarbons (THC)	Carbon Monoxide (CO)	Nitrogen Oxides (NOx)	Methane (CH4)	Volatile Organic Compounds (VOC)	Particulate Matter < 2.5µm (PM2.5)	Brakewear (PM2.5)	Tirewear (PM2.5)	Energy/Carbon Dioxide (CO2)
100% Human - 2400 vlh	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
100% CACC - 2400 vlh	-41.9%	-50.0%	-22.9%	-55.0%	-39.5%	-21.7%	-88.8%	-3.0%	-6.4%
50% Human/50% CACC - 2400 vlh	-22.3%	-31.7%	-13.0%	-28.5%	-21.2%	-21.1%	-41.8%	-1.7%	-4.7%
100% CACC - 4000 vlh	-45.6%	-58.7%	-27.2%	-59.6%	-43.0%	-29.8%	-84.4%	1.7%	-8.3%

Figure 22: A bar chart and table of percent reductions in energy and emissions per vehicle from 100% human (baseline) driving on an idealized highway segment

In absolute terms, the inventories for NOx, PM, and energy would increase in the high-volume 100% CACC scenario. As a thought experiment, we added the following number of automated vehicles in Table 9, below, for comparable results as baseline human driving. With these changes in driving behavior from CACC systems, this means that one could expect roughly equivalent energy consumption and emissions despite a higher throughput of vehicles.

Table 8: Potential number of vehicles added for comparable energy consumption and emissions as baseline driving on an idealized highway segment

	NOx	PM2.5	Energy	Total
Human Baseline (vehicles/hr)	n/a	n/a	n/a	4976
AVs to Add (vehicles/hr)	1711	1833	345	3889

5.3.3 Study 3: CACC and Wiedemann Scenarios on I-91 Network

As described in our latest publication, we have developed three scenarios of passenger cars on I-91 northbound near Springfield:

1. Baseline driving behavior with Vissim's default Wiedemann 99 car following model, meant to emulate human drivers;
2. CACC driving behavior according to an adjusted MIXIC model car following model developed for FHWA; and
3. Modified baseline driving behavior where the Wiedemann 99 traffic oscillation parameters have been set to zero.

Despite modest changes to network performance metrics, especially delay and headway, CACC systems produce substantial changes to operating mode distributions and subsequent emissions from the baseline Wiedemann 99 driving behavior.

The results follow the same trends across all pollutants and energy use. For comparison, we generated plots of the link-level energy and emission impacts across the 45 microsimulations on the I-91 network normalized per vehicle, as shown in Figure 23. Our analysis presents results for energy consumption/carbon dioxide (CO_2) and particulate matter with diameters of 2.5 microns or less (PM2.5). Impacts varied more by link than pollutant for the three scenarios. On average, some links saw emission and energy benefits, namely on Link 101 and 104, for the CACC scenario over the baseline, and other links saw dis-benefits, namely Link 100 and 103. CACC systems appear to perform well in congestion and not as well on links prior to congestion. The Wiedemann scenario without oscillations had mixed results, where it was often as likely to produce benefits as dis-benefits. We found marginal energy/CO_2 for Link 100 and 103.

Pairing the energy and emission results by seed, enables the calculation of the percent reductions for each scenario from the baseline on the I-91 Springfield network. Table 10 below shows the mean percent reductions and standard deviations for the CACC and Wiedemann without oscillations scenarios for carbon monoxide (CO), nitrogen oxides (NOx), fine particulate matter (PM2.5), and volatile organic compounds (VOC) as well as carbon dioxide (CO_2) and energy consumption. Our findings suggest that CACC driving will lead to sizable CO, PM, and VOC benefits along with slight NOx benefits but will not improve fuel efficiency over the baseline. The Wiedemann scenario, however, leads to negligible or no benefits from the baseline.

Table 9: Mean and standard deviation of energy, CO, NOx, PM2.5, and energy/CO2 benefits (percent reductions) on the I-91 network for the CACC and Weidemann scenarios from the baseline over the 15 random seeds

	CACC from Baseline		*Wiedemann from Baseline*	
Pollutant	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**
CO	20.12%	±3.85%	-0.84%	±6.64%
NOx	2.53%	±2.20%	1.59%	±3.21%
PM2.5	25.24%	±4.05%	-3.35%	±7.55%
VOC	10.41%	±2.89%	1.71%	±4.61%
Energy/CO_2	-0.23%	±1.38%	0.25%	±1.97%

Based on our results above, using an independent driving behavior model for simulating specific CAV technologies appears to be preferable over changing the default microsimulation parameters to mimic CAV driving. While this paper only examines CACC systems, the Modeling Framework enables the assessment of other SAE J3016 Level 1 automation technologies or combinations thereof, such as:

- Dynamic speed harmonization,
- Platooning,
- Lane keeping assistance, and
- Cooperative lane change.

Driving behavior models can also be calibrated and validated against field tests of instrumented vehicles as the CAV technologies become available. Using MOVES, this study has developed a streamlined process to evaluate energy and emission impacts of multiple microsimulations of CAVs with high-resolution, 10 Hz vehicle trajectory data through an external Python tool.

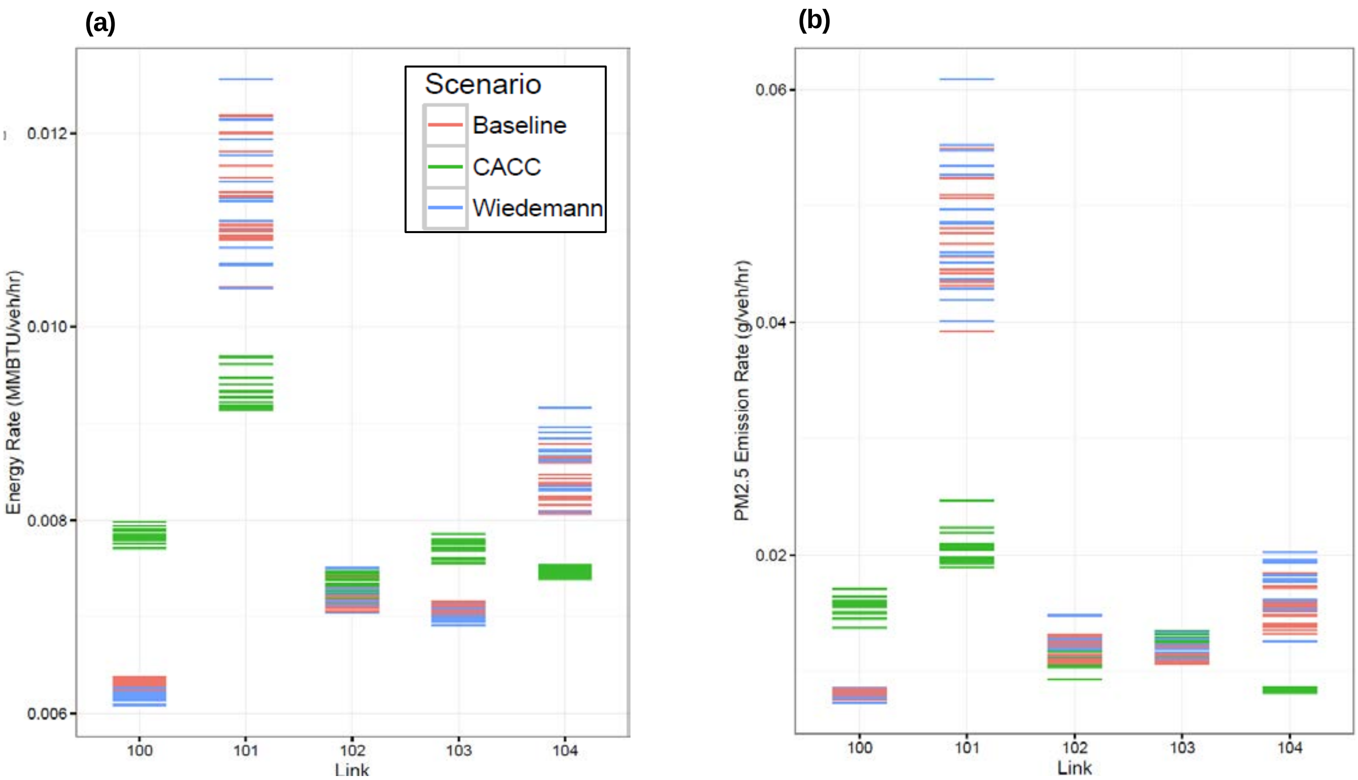


Figure 23: Volume-normalized link-level energy and emission results by I-91 link for each of the 45 simulations for (a) energy/CO2 and (b) PM2.5

Although this research presents some promising outcomes in the reduction of environ / emissions, it does not address issues associated with higher levels of driving automation (e.g., SAE Level 3 and above). Changes in vehicle ridesharing and ownership, routing and mode choice, and even land use due to self-driving and driverless vehicles will undoubtedly lead to other environmental effects. This work could also potentially be extended to evaluate CAV noise benefits due to reduced accelerations and decelerations. Continuing in our research, we plan to examine higher levels of congestion and different CAV penetrations, further investigate lane changing, test other driving behavior models, and utilize more network-specific data in MOVES to refine this Modeling Framework.

Chapter 6 Economy and Jobs

Increasing levels of vehicle automation may create significant improvements in road safety by reducing the large share of vehicles crashes that are associated with some form of driver error, inattention, or impairment. Automation-enabled applications such as cooperative adaptive cruise control, platooning, and eco-driving can also yield improvements in traffic flow, fuel use, and emissions. Each of these impacts has value to society in the form of reducing the costs of crash-related injuries, reducing the time and money costs of travel, enabling access to valued destinations, and reducing the health-related and environmental consequences of vehicle emissions. While the exact magnitude of these impacts is not known at this time, they can be estimated using modeling and simulation tools, and then converted to monetary terms for the purposes of benefit-cost analysis (BCA).

6.1 Impacts on Economic Growth

BCAs for conventional transportation projects do not typically include broader macroeconomic impacts, since these impacts are usually small and diffuse. For example, replacing a set of four-way signalized intersections with roundabouts may improve safety and travel times, but is unlikely to create measurable changes in economic output at the national or even regional scale. However, some large-scale investments and transformative technologies do have the potential to affect overall economic growth, as in the much-studied cases of the Erie Canal, the transcontinental railroad, and the Interstate Highway System among others.

There are several plausible mechanisms by which automated vehicles could affect economic output through influences on the determinants of economic growth, i.e. on labor supply, capital stock, and productivity. One mechanism is through increased labor supply: Level 5 automation (fully self-driving vehicles) would remove barriers to job access for large numbers of people who cannot drive due to disability, thereby increasing their labor force participation. Traffic safety improvements and the availability of automated transport services could also mean fewer working hours that are lost to crash-related injuries and delays, to other forms of congestion, and to the demands of "chauffeuring" children or elderly relatives. Some portion of these time savings may be redeployed into paid employment, increasing labor supply and overall economic output.

Vehicle automation could also be expected to yield improvements in the productivity of labor. For example, when relieved of most or all hands-on driving responsibilities, travelers could spend a portion of their workday in more productive activities. A property assessor or salesperson who normally devotes part of the workday to driving between sites could instead use the time to complete paperwork or contact clients (Executive Office of the President, 2016). Electricians, plumbers, and other tradespeople may be able to conduct additional service calls during the course of a normal workday to the extent that AVs reduce congestion and thus the time required to move between jobsites. Within the transportation sector, a single employee at a control center could potentially monitor multiple automated trucks or buses, rather than each vehicle requiring its own operator, which would represent a major increase in labor productivity.

Another potential impact on productivity is that improved travel speeds can increase workers' effective commuting radius – that is, a larger number of jobs will be geographically located within an acceptable commute time of the employee's home. This enables better matching of workers to job requirements, and thus – at least in theory – can foster greater division of labor and higher productivity (Timothy, D. & Wheaton, W.C., 2001). An example of this would be a physician who could earn higher wages as a sports-medicine specialist in a larger market such as New York City, but who wishes to remain in rural Connecticut for family reasons. The prospect of high-speed AV travel over uncongested (or at least less-congested) roadways, with the ability to sleep or multitask while en-route, could make the daily commute to Manhattan viable in a way that it currently is not.

While each of these mechanisms is plausible, the extent to which these labor market impacts would actually occur as a result of AV adoption, as well as their magnitude and the timescale over which they would play out, is unclear and would require significant additional research. AV technology is currently at a stage where the direct transportation system impacts on which these secondary impacts are predicated – reduced crashes, improved traffic flow, new modes of travel – are plausible but have yet to be realized in any sort of large scale, real-world setting. Moreover, the most significant impacts appear to be associated with fully driverless vehicles (Level 4 or Level 5 automation) rather than with driver assistance functions, and thus may be expected to emerge over the course of decades rather than years.

Existing research in the area of AV-related impacts on productivity is fairly limited, although there have been some initial efforts to outline the effects of vehicle automation on overall economic activity and specific sectors (Fagnant, D. & Kockelman, K., 2014). Other existing work analyzing the impacts of conventional transportation investments on overall productivity and output (see for example, (Puckett, S., 2015)) may also be transferable to the case of automation.

There is also research on other applications of automation and artificial intelligence across the economy as a whole. A 2015 study on robotics found that it has added approximately 0.4 percentage points to GDP growth across a set of 17 countries for the period 1993 to 2007 (Graetz, G. & Michaels, G., 2015) cited in (Executive Office of the President, 2016)). While robotics is widely recognized as a potential contributor to productivity growth, at this stage the major economic forecasting firms do not appear to be making adjustments to their forecasting models to explicitly account for any productivity or other impacts from AV adoption.

6.2 Impacts on Employment and Wages

A recent report by the Executive Office of the President (EOP) addresses the potential impacts of automated vehicles within the larger context of artificial intelligence (AI) and robotics (Executive Office of the President, 2016). The authors note that technological innovations have been a key driver of economic growth throughout the nation's history. It that sense, AI is simply the most recent wave of technological change, with each wave bringing enhanced productivity and rising overall living standards, but also causing significant disruptions to established industries and often leading to greater income inequality.

Despite the impressive progress that AI algorithms have made, they are generally most amenable to routine tasks that do not require sophisticated human judgment or abstract reasoning and problem-solving. The workers at greatest risk for being replaced by automation in the near- to medium-term are therefore generally those at lower skill levels. EOP combined the results from a 2013 survey of AI experts on the automation prospects for various job tasks with data on average earnings, and found that roughly 83 percent of jobs earning less than $20 per hour would be at risk from automation, versus only 31 percent for jobs in the $20-$40 per hour range, and a mere 4 percent of jobs earning over $40 per hour. This pattern is consistent with the skill-biased technological changes that have been observed since the mid-1970s related to advances in computing and telecommunications.

Within the transportation sector more specifically, the EOP report draws on statistics from the Bureau of Labor Statistics to estimate that approximately 2.2 to 3.1 million driving-related jobs (part- and full-time) are at risk due to automated vehicles. This represents roughly 1½ to 2 percent of total nonfarm employment, and includes job classifications such as transit bus driver, inter-city bus driver, school bus driver, light truck and delivery driver, heavy truck driver, taxi drivers, and chauffeurs. An additional affected job category, not included in BLS totals but estimated separately by EOP using other research, comprises drivers for transportation networking companies (ride-hailing services), such as Uber, Lyft, and Fasten. A separate analysis by the Center for Global Policy Solutions (CGPS) using American Community Survey data arrived at a slightly higher total of 4.1 million driving jobs potentially at risk from automation (Center for Global Policy Solutions, 2017).

A detailed analysis from the Department of Commerce, which looked at driving-related duties by occupation, arrived at a similar figure of 3.8 million workers in occupations for which driving is a primary activity, and noted that these workers are more likely to be displaced by automation than other occupations (Beede, D.R., Powers, R., & Ingram, C., 2017). An additional 11.7 million workers are in occupations that have a driving component, such as repair and installation, construction, and home health aides. These workers may see productivity gains related to automation of the driving portion of their workday (Beede, D.R. et al., 2017).

While each of these studies agrees on the general magnitude of the potential employment impacts, the timeframe for these changes is less clear. One analysis that does mention specific dates comes from the International Transport Forum, which estimated that demand for truck drivers could be reduced by as much as 50 to 70 percent by 2030 across the United States and Europe (International Transport Forum, 2017). The time required for a transition to fully driverless operation is the subject of considerable debate within the research community, given the many technology and policy challenges (Shladover, S.E., 2014).

EOP's analysis finds that potential job losses to automation will vary considerably across occupational classifications. Jobs with non-driving components that are less amenable to automation, such as a school bus driver's monitoring of pupils, are less likely to be replaced by automation; EOP estimates that roughly 30 to 40 percent of such jobs are at risk. Conversely, heavy truck drivers – the single largest category of driving jobs – are estimated to have higher risk of job loss, at 80 to 100 percent, due to the relative lack of such non-driving functions. Beyond these direct effects, EOP notes that workers with little connection to either driving or automation could nonetheless be affected, for example if large numbers of displaced drivers enter the market for lower-skill jobs and create downward pressure on wages. It is also possible that some driving-related jobs would be transformed into vehicle attendant or monitoring positions with lower wages.

CGPS' analysis highlights the fact that minority groups (African-Americans, Hispanics, and Native Americans) are over-represented among driving occupations and that, for these groups, average earnings are higher in driving-related occupations than in non-driving occupations (the reverse is true overall). This suggests that losses of driving jobs due to automation will have disproportionately large negative impacts on employment and wages for these demographic groups.

There are also many potential positive job-market impacts from AVs and automation, including new employment opportunities in programming and supervision of automated technologies and in emerging areas such as cybersecurity. At high levels of automation, fundamental aspects of vehicle design could also be altered, for example with workspaces replacing vehicle controls, creating additional demand for engineers and designers. With AVs potentially opening up new areas such as remote parking, automated delivery, or mobile offices, new markets and job opportunities could emerge. Moreover, as EOP's report notes, the history of technological change in the US is such that the generally rising overall incomes associated with higher productivity will translate into additional demand for a wide spectrum of products and services.

6.3 Impacts on Industries

6.3.1 Automotive and Related

Within the automotive industry, automation is already beginning to change product offerings and introduce competitive pressures for advanced safety and convenience features. Some Level 1 safety functions such as automatic emergency braking, while originally introduced in a small group of luxury vehicles, are now widely available on a wide variety of new vehicles at almost all price levels. Level 2 functions combining longitudinal and lateral control may be the next to make this transition.

Vehicle-to-vehicle (V2V) technology is on track to be in 50 percent of new vehicles by 2022, according to a Juniper Research report. This equates to 35 million total V2V consumer vehicles on the road by that same year (Juniper Research, 2017). Not all AV components, however, are approaching the same level of market penetration as V2V. LiDAR is a type of sensor that most AV researchers are now using and the demand currently outweighs the supply. Companies have to wait months for new LiDAR sensors, and these sensors can be expensive, costing tens of thousands of dollars. At least one manufacturer is working on a less expensive device that may be more practical for deployment (Simonite, T., 2017).

To date, however, automation has arguably not progressed to the point where it would change the fundamentals of the automotive market, such as sales volumes or profitability. Over the longer term, as fully driverless vehicles emerge, impacts on the industry will depend in large part on the ownership and mobility paradigm that develops. One possibility is something akin to the status quo, in which most vehicles continue to be privately owned by households and operated for their exclusive use. In this case, the business model may continue largely as it is now, but with potential changes to fleet turnover due to changes in VMT and vehicle ownership rates, along with fewer severe crashes. Conversely, in a future scenario in which many travelers – particularly in urban areas – use on-demand or “mobility as a service” concepts in lieu of owning their own vehicle, the prevalence of shared fleets could change the economics of the automotive industry. In particular, simulation results typically show that a metropolitan area could be served with a much smaller vehicle fleet than at present, since the vehicles would be used much more intensively to serve passenger trips rather than remaining parked for most of the day (Burns, L.D., Jordan, W.C., & Scarborough, B.A., 2013). While this might suggest lower sales volumes, the other side of the coin is that annual mileage per vehicle would be substantially higher, leading to more rapid fleet turnover. This pattern of higher vehicle utilization, in turn, could also lead to engineering changes that improve durability or other changes to the product development cycle. Some analysts have suggested that automobiles that are purpose-built for the AV-taxi (shared mobility) market, rather than as personal or family vehicles, could also have simplified designs and lower horsepower, resulting in cost reductions of around 25 percent.

Many automakers are already partnering with or acquiring mobility service providers, which could change the automotive landscape for companies and consumers. Car sales tend to be very cyclical, meaning automakers can face sharp declines in sales and profits during recessions. Ride-sharing, however, could help offset that downturn, by allowing automakers to produce ride-sharing revenues during periods when automobile sales are down. Ford recently acquired Chariot, an on-demand shuttle service that began in Silicon Valley and is slowly expanding (Miller, D., 2017). In early 2016, General Motors announced its $500 million investment in the ride-sharing startup Lyft, which also gained GM a seat on Lyft’s board of directors. GM and Lyft are partnering to create a network of autonomous vehicles for ride-sharing purposes (Davies, A., 2016). Waymo – Google’s AV development company – has also signed a deal with Lyft (Isaac, M., 2017).

Many automakers and other AV-focused companies are investing in mobility service providers, but the extent to which shared mobility services may supplant conventional vehicle ownership depends on a number of economic, technology, and policy variables that are difficult to forecast. In the near- to medium-term, many industry analysts expect continued strong growth in the shared mobility sector but with only modest impacts on vehicle sales (Grosse-Ophoff, A., 2017). In part this is due to the difficulties of serving the US market, which includes many suburb-to-suburb trips and trip-chaining behavior that is not well-suited to shared mobility services (Grosse-Ophoff, A., 2017). It is important to keep in mind that market share for shared mobility services is currently very low, at less than 1% of all vehicle-miles traveled, so these services can grow substantially from their small base while still having relatively little influence on overall sales patterns.

It is also true, however, that data from the U.S. National Household Travel Survey (NHTS) suggests that less than 17 percent of household vehicles that are 10 years old or less are in use at any given time (Fagnant, D., 2014). Multiple studies and models have tried to estimate the impact that car-sharing could have on personal vehicle ownership, as consumers may begin decide that owning their own car is no longer as advantageous as using a shared mobility service. Results from a Center for Automotive Research study, which looked at all of North America, estimated that one car-sharing vehicle would replace 7.1 private vehicles in 2021. Additionally, the study estimates that 164,606 vehicle sales will not be made between 2010 and 2021 due to car-sharing (Spulber, A. et al., 2016).

A report by RethinkX goes much further, estimating that 95% of miles traveled will be inside autonomous electric vehicles by 2030, and that these AVs will be owned by service providers, not the passengers themselves. The report argues that some forms of AV-related cost savings have been overlooked by other studies. RethinkX looks at the cost reductions from the combination of AV and electric vehicle technology to support its analysis (Arbib, J. & Seba, T., 2017).

Although automation is strictly speaking a separate question from fuel and propulsion systems, it is possible that a transition to highly automated vehicles would be associated with increased adoption of electric vehicles. There are some synergies between the two sets of technologies, for example with EVs typically using brake-by-wire and throttle-by-wire rather than mechanical linkages, which is more amenable to automated control (Energy Information Administration, 2017). The ability of fully automated vehicles to self-reposition for recharging would also address one of the current limitations of EVs. Other AV-related changes could change the basic economics of the EV purchase decision; for example, higher annual mileage per vehicle would make it more likely for the EV price premium to be recouped through future fuel savings. These impacts depend strongly on variables such as fuel prices and environmental policies.

The automotive maintenance and repair fields may also experience changes, for example if advanced safety systems result in reduced collisions and associated body work (Clements, L.M. & Kockelman, K., 2017). As of March 2017, the U.S. Census Bureau reported total employment in the automotive repair and maintenance industry at around 920,300, and total employment has been on an upward trend since 2010 (Bureau of Labor Statistics, 2017). But those numbers could fall, depending on how autonomous systems affect vehicle crash rates and maintenance needs. Even without full autonomy, vehicles with autonomous pre-crash braking can avoid crashes, or reduce the velocity at which the crash occurs, reducing repair costs. In a series of crash tests with BMW and KTI, a repair research company in Germany, researchers found that repair costs were reduced by more than 29% with vehicles that had pre-crash braking at a collision speed of 64 km/h, and costs were reduced even further, to 37%, at a collision speed of 38 km/h (Kiebach, H., 2013). Reductions in crash rates and repair costs could reduce the demand for automotive repair, but it is also possible that the sophisticated electronics on highly automated vehicles may require more routine maintenance and/or enable additional options for remote diagnostics.

Auto insurance is also likely to evolve as AVs reduce crash rates but potentially create higher vehicle repair costs per incident due to the presence of expensive sensing equipment. One analysis describes a potential loss of premium revenues for insurers (Clements, L.M. & Kockelman, K., 2017), but since premium rates are set in reference to expected claims, there does not seem to be a major issue for industry profitability, and indeed IIHS and other industry stakeholders have strongly supported the rollout of partial-automation safety functions such as automatic emergency braking. Although AVs may yield a large reduction in collision clams, this transition will take decades to unfold due to the continuing presence of non-automated vehicles. Insurance policies will continue to be needed as a backstop, as well as for theft, weather damage, and other comprehensive claims. However, the insurance industry has begun analyzing possible changes to the types of policies and coverage that may be needed in response to changes in technology and business models (Energy Information Administration, 2017). A NHTSA investigation found that Tesla's Autopilot or Autosteer semi-autonomous technology reduced overall crash rates by 40 percent, relative to other Tesla vehicles without the technology (Habib, K., 2017). Root, an insurance startup, has extended discounts to Tesla vehicles that have the Autopilot technology, though other insurers have argued that Tesla has higher claim frequencies (Burke, K., 2017). Another potential market evolution is that insurers may shift from covering consumers to covering auto manufacturers who face liabilities when their AVs experience technical failures (Bertoncello, M. & Wee, D., 2015).

6.3.2 Passenger and Freight Transportation

Automated vehicles will have impacts on other transportation industries through their influence on mode choice decisions for passengers and freight. At the margin, lower generalized travel costs for AVs would increase the attractiveness of the automobile and trucking modes relative to competitors such as air, rail, and maritime transportation. However, the magnitude of these impacts is unclear, and each competing mode has unique characteristics that make large-scale changes unlikely. For example, rail and vessel freight will likely still be the most cost-effective options for moving heavy cargoes over long distances, and air transportation is likely to retain its dominant position for long-haul and transoceanic passenger travel. For moderate-value cargoes moving over long distances, where rail and truck compete, there may be some modal shift to truck. Automation is also taking root in these fields as well, leading to potentially lower transport costs and higher efficiency that would match the advances made with AVs.

However, some portions of the market may experience more significant changes, such as short-haul air and rail travel. Relative to air travel, AVs would retain the current advantages of automobile travel – including greater schedule flexibility, point-to-point routing, and the absence of time-consuming check-in and security screening requirements – while also adding the ability to work or rest enroute. Highway travel times may also be reduced to the extent that widespread adoption of AVs reduces congestion and/or enables safe operation at higher speeds. A similar phenomenon has been observed with the introduction of high-speed rail services that significantly reduce demand for short-haul air routes (e.g., Paris to Brussels). At the same time, the potential availability of on-demand AV taxi-like services may spur additional trip-making by air and rail, by lowering the overall cost of travel, and by reducing the need to have one's own vehicle available for use at the destination.

6.3.3 Other Industries

While the principal impact of AVs would be on the automotive industry and the transportation sector, other industries could also experience AV-related changes. A study from Intel and Strategy Analytics estimated that AVs will be part of a $7 trillion market by 2050, of which nearly $4 trillion would come from driverless ride-hailing and another $3 trillion from driverless delivery and business logistics. However, the authors estimate that an additional $203 billion could come from impacts in other sectors, including healthcare and tourism (Lanctot, R., 2017).

One direct mechanism for AVs to influence the healthcare industry is simply through improved access, as transportation-related barriers are common. A review of past studies found that 10 to 51 percent of patients reported that transportation was a barrier to their access to care (Syed, S.T., Gerber, B.S., & Sharp, L.K., 2013). AVs could address barriers for at least some of these patients – for example, those who cannot drive due to age or disability, or cannot use conventional public transportation, but could afford either a personal AV or taxi-like service in a shared AV. Some researchers have also posited that AVs could act as medical devices themselves, for example by detecting or predicting cardiac events (Gunaratne P, Ebe K, Horan K, Najarian K, Soroushmehr S.M.R, 2017).

Impacts on the other industries are more difficult to predict, but have been the subject of some research and analysis. One key impact is that travelers who use fully automated vehicles would potentially have large blocks of free time during their daily commutes. A McKinsey & Company study has suggested that AVs could free 50 minutes a day, where each additional minute while in an AV could generate revenues of around $5.6 billion per year, if passengers choose to use mobile internet during that time (Bertoncello, M. & Wee, D., 2015).

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Appendix A. List of Acronyms

Abbreviation	Term
ACC	Adaptive Cruise Control
AD	Automated Driving
AI	Artificial Intelligence
AV	Automated Vehicle
BCA	Benefit-cost Analysis
BLS	Bureau of Labor Statistics
BSW	Blind Spot Warning
BTU	British Thermal Unit
CACC	Cooperative Adaptive Cruise Control
CGPS	Center for Global Policy Solutions
CO	Carbon Monoxide
CO_2	Carbon Dioxide
DOT	Department of Transportation
DSRC	Dedicated Short Range Communication
EOP	Executive Office of the President
EPA	Environmental Protection Agency
EV	Electric Vehicle
FCW	Forward Collision Warning
FESTA	Field opErational teSt supporT Action
FHWA	Federal Highway Administration
FOT	Field Operational Test
FTA	Federal Transit Administration
GDP	Gross Domestic Product
GHG	Greenhouse Gas
IDM	Intelligent Driver Model
IIA	Independence of Irrelevant Alternatives
IIHS	Insurance Institute for Highway Safety
ITS JPO	Intelligent Transportation Systems Joint Program Office
IVBSS	Intelligent Vehicle Based Safety Systems
IVTT	In Vehicle Travel Time
KPI	Key Performance Indicator
L1,L2,L3,L4,L5	Levels of automation (See SAE J3016)
LDW	Lane Departure Warning
MIXIC	Microscopic Model for Simulation of Intelligent Cruise Control
MOVES	Motor Vehicle Emission Simulator
MPO	Metropolitan Planning Organization
NCHRP	National Cooperative Highway Research Program
NHTSA	National Highway Traffic Safety Administration
NOx	Oxides of Nitrogen
ODD	Operational Design Domain
OVTT	Out of Vehicle Travel Time
PM	Particulate Matter

Abbreviation	Term
POV	Privately Owned Vehicle
SAE	Society of Automotive Engineers
SBIR	Small Business Innovation Research
SIM	Safety Impact Methodology
SIP-adus	Strategic Innovation Promotion – Automated Driving for Universal Service
TRB	Transportation Research Board
TTC	Time to collision
U.S. DOT	United States Department of Transportation
V2V	Vehicle-to-vehicle
V2X	Vehicle-to-anything
VMT	Vehicle Miles Traveled
VOC	Volatile Organic Compounds
VSP	Vehicle-Specific Power

Appendix B. SI Conversion Factors

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: volumes greater than 1000 L shall be shown in m^3				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
oz	ounces	28.35	grams	g
TEMPERATURE (exact degrees)				
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
ILLUMINATION				
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
FORCE and PRESSURE or STRESS				
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
LENGTH				
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
AREA				
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
VOLUME				

SI* (MODERN METRIC) CONVERSION FACTORS

mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
mL	milliliters	0.034	fluid ounces	fl oz
MASS				
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
g	grams	0.035	ounces	oz
TEMPERATURE (exact degrees)				
^oC	Celsius	1.8C+32	Fahrenheit	^oF
ILLUMINATION				
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
FORCE and PRESSURE or STRESS				
N	newtons	0.225	poundforce	lbf
kPa	Kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with section 4 of ASTM E380. (Revised March 2003)

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