Benefits Estimation Framework for Automated Vehicle Operations

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ITS JPO project manager is Kevin Dopart

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 presents a framework for estimating the potential benefits and dis-benefits of technologies contributing to the automation of the Nation's surface transportation system. Components of the framework include (1) **Safety:** exposure to near-crash situations, crash prevention, and crash severity reduction; (2) **Vehicle mobility:** vehicle throughput, both in car following situations and at intersections; (3) **Energy / environment:** fuel consumption and tailpipe emissions; (4) **Accessibility:** personal mobility, for motorists and nonmotorists; (5) **Transportation system usage:** response of travelers to changes in mobility and accessibility, as well as potential new modes of transportation such as increased car sharing; (6) **Land use:** effects of automation on land use, and (7) **Economic analysis**: the macro-economic impacts of all of the above changes.

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Executive Summary

Automated vehicles (AVs) have the potential to bring about transformative safety, mobility, energy, and environmental benefits to the surface transportation system. These benefits could include crash avoidance, reduced energy consumption and vehicle emissions, reduced travel times, improved travel time reliability and multimodal connections, improved transportation system efficiency and improved accessibility, particularly for persons with disabilities and the growing aging population (Dopart, 2015).

AVs are also being introduced into a complex transportation system. Second-order impacts, such as the possibility of increased vehicle-miles traveled (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 will be used to help shape Federal policy to increase the likelihood that automated vehicle technologies actually do bring the expected benefits to the Nation's transportation system.

This report presents a framework for estimating the potential safety, mobility, energy, and environmental benefits (including potential dis-benefits) of technologies contributing to the automation of the nation's surface transportation system. Users of the framework will include anyone who wishes to use quantitative analysis to better understand the impacts of automated vehicle scenarios. Federal and State Departments of Transportation (DOTs) may use it to support policy analysis. State DOTs and metropolitan planning organizations (MPOs) may use it for long-range scenario-based planning, where various automation futures are envisioned. Automakers and after-market equipment manufacturers may use it to better understand the potential benefits of their offerings.

Overall Vision

The modeling framework is a comprehensive approach for quantitative assessment of the wide-ranging impacts of various automation scenarios. These scenarios serve as inputs to the framework. The outputs are intended to help inform policy decisions.

This framework has the following characteristics:

1. It is designed to facilitate the comparison of multiple scenarios. For example, scenarios can be used to address the degree to which vehicles are connected with each other and with the infrastructure, as well as facilitating a comparison of different levels of automation.
2. It will include a number of submodels (Figure ES-1), to address the various benefit areas.
3. It will address multiple time scales, ranging from second-by-second vehicle performance to multi-year impacts.
4. It will use existing models, where possible, to address the various aspects of automation and benefit areas.
5. It will be built incrementally, so that some initial results will be available within a reasonable timeframe.

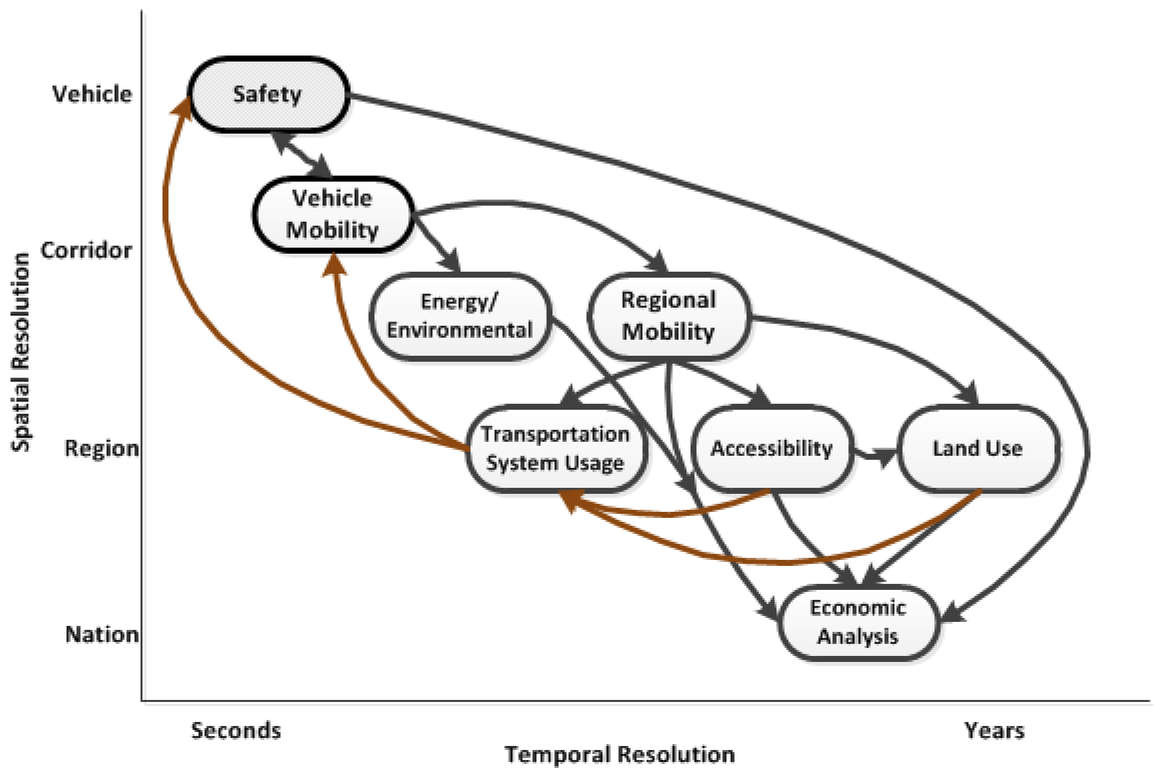

Figure ES-1. Components of the Modeling Framework (Source: U.S. DOT)

Submodels

The submodels in Figure ES-1 include the following:

Safety

Safety modeling primarily deals with the behavior of driver/vehicle/automation system in the seconds leading up to a potential crash. Thus, safety modeling tends to be performed at an extremely fine-grained level of spatial and temporal resolution, with the results being rolled up into national benefits.

The primary measure of safety is crashes, which are typically categorized by severity (property damage only, various levels of injury, fatality), and normalized by population, vehicle-miles traveled, or person-miles traveled.

Safety modeling will be based on Safety Impact Methodology (SIM) (Najm & daSilva, 2000) (Carter, Burgett, Srinivasan, & Ranganathan, 2009), which is a systematic approach for evaluating the safety impacts of a new vehicle system. The SIM incorporates historical crash, driver performance, and system performance data to enable a rigorous comparison of baseline and treatment vehicle crash conflicts. It has been used, for example, to assess the safety impacts of Vehicle-to-Vehicle (V2V) technologies (Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014).

Vehicle and Regional Mobility

Vehicle mobility deals with car following, gap acceptance, and other detailed aspects of vehicle performance. Regional mobility is at a less fine-grained spatial and temporal resolution, and deals with the performance of a highway corridor, an intersection, or a region.

Measures include car-following headways and freeway or intersection hourly lane capacities. At a regional level, mobility measures may include the mean and 95^{th} percentile travel times on a corridor, as well as average speeds, travel times, and various congestion indices for a region.

At a vehicle level, mobility is typically modeled via detailed microsimulation. A meso-scale model, such as a dynamic traffic assignment model, may be used for regional mobility.

Energy / Environmental

A detailed driving cycle (idle time, acceleration, cruise, deceleration) that comes from the mobility modeling is input to a model that calculates energy consumption and emissions.

Measures include vehicle and personal energy consumption, tailpipe carbon dioxide (CO_2) emissions, and tailpipe criteria pollutant[1] emissions.

The planned modeling approach is to link the driving cycle information from the mobility modeling to the Environmental Protection Agency's Motor Vehicle Emissions Simulator (MOVES2014) model.

Transportation System Usage

Travelers will change their travel patterns in response to changes in mobility (for example, if a road becomes less congested, it may receive more use). This part of the framework captures the traveler responses to changes in mobility and accessibility. As such, it drives most of the feedback (depicted as the brown lines in Figure ES-1).

Measures of transportation system usage include both vehicle mobility (congestion) and personal mobility (number of trips made and accessibility of desirable destinations).

Metropolitan Planning Organizations and State DOTs have been modeling transportation system impacts for close to 50 years, primarily in support of long range planning. The proposed approach is to use this existing framework as much as possible, while addressing the changes that automation will bring.

Accessibility

Accessibility measures the ability of people to reach desired destinations. One direct measure of accessibility is the number of jobs or other desired destinations that can be reached from a household, weighted by the time (or generalized cost) required to reach them. The introduction of fully automated vehicles could bring large benefits in accessibility, particularly for non-drivers. For the purposes of this framework, we will consider accessibility as part of the regional transportation modeling process.

Land Use

Land use addresses the density and mix of development in a particular region. Personal transportation choices such as VMT levels and mode choice are strongly influenced by development patterns, and much of the urban

[1] Criteria pollutants include ozone, particulate matter, carbon monoxide, nitrogen oxides, sulfur dioxide and lead. See http://www.epa.gov/airquality/urbanair/

landscape is devoted to accommodating transport functions such as car parking, streets, highways, and transit systems. As such, widespread adoption of automated vehicles, particularly at higher levels of automation, could have significant impacts on future land use.

Overall, the impacts of automation on land use are beyond the scope of the initial analysis and will continue to present analytical challenges for some time. However, some understanding of the potential mechanisms for land use changes is important, especially since land use will, in turn, have longer-term influences on travel demand, emissions, and other impacts studied here.

Economic Analysis

Many of the other benefits, including reduced cost of crashes and congestion and improved access to jobs, lead to economic benefits. Economic modeling is planned as a follow-on to the other modeling efforts as described above.

Next Steps

During the development of this framework, we have received valuable input from various stakeholders, particularly within the modal agencies of U.S. DOT. These partnerships should be continued.

The next step will be to build the initial iteration of an AV Benefits model. We will identify the primary data sources, assumptions, and define the specific scenarios that will be analyzed. Taken together, this information will define the scope of our overall analytical model, and thereby the requirements of each submodel (e.g., mobility, safety, etc.). To finalize this planning phase of model development, we will develop a report that lists our data sources, the justification of our assumptions, and defines the scope statement of the model.

Upon acceptance of our model's scope statement, we will develop or obtain access to the necessary modeling tools. While some of these models may already be accessible to our team, or are commercially available, we believe that some models will need to be developed or adjusted either through in-house resources or a third-party partnership. Initially our focus will be on the development of the safety and mobility models, followed immediately by the energy and environmental model. We have chosen this stepwise approach to minimize interface/compatibility issues between the models, and to reduce the timeframe for communicating our findings. Furthermore, by starting with these models, we will have the opportunity to compare/validate our results against previously published research findings, particularly for lower levels of automation such as cooperative adaptive cruise control (CACC). Further iterations of the model will incorporate additional scenarios and demonstrate the impacts from the other submodels on regional transportation usage and land use.

Chapter 1 Introduction

Automated vehicles have the potential to bring about transformative safety, mobility, energy, and environmental benefits to the surface transportation system. These benefits could 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 accessibility, particularly for persons with disabilities and the growing aging population (Dopart, 2015).

Reasons for these benefits include, potentially,

- The reduction of crashes due to human error
- Dramatically improved throughput via reduced vehicle following distances and other improvements in vehicle operations and traffic management
- Improved mobility for those unable or unwilling to drive, and
- Reduced fuel consumption and associated environmental impacts.

While the benefits of automation could be potentially large, the actual benefits to be realized will depend on system performance and driver interaction in the real world.

This report presents a framework for estimating the wide range of positive and negative impacts of the technologies contributing to the automation of the nation's surface transportation system.
The remainder of this report describes the framework. It is organized into the following sections:

- Section 1 (this section) presents the purpose of the framework, intended users and the overarching vision.
- Section 2 discusses the areas to be addressed (safety, mobility, etc.) and proposes some measures for each of these dimensions.
- Section 3 discusses the specific automation applications to be addressed.
- Section 4 describes the modeling framework in more detail.
- Section 5 outlines a proposal for initial model development.

Purpose of the Modeling Framework; Objectives and Goals

The goal of this project is to develop a framework to estimate the potential safety, mobility, energy and environmental benefits (including potential dis-benefits) of technologies contributing to the automation of the nation's surface transportation system.

In the area of safety, the framework should help to answer the following questions:

- What aspects of automation provide sufficient benefit so that they should be encouraged for further development and/or implementation?
- What aspects of automation create enough risk of negative impact (including side effects and changes in driver behavior) to warrant policy action to mitigate the risk?
- Might the safety benefits be great enough to warrant the encouragement of smaller, lighter vehicles?
- To what extent will safety benefits depend on connected vehicle (V2V, V2I and V2P) systems?

For automation applications that are well understood, and if sufficient data are available, the framework should support modeling that is rigorous enough to help justify a policy response.

In the area of mobility, the framework should help to answer the following questions:

- Given a particular scenario[2], what mobility benefits, if any, will occur with improved car following, at intersections or elsewhere?
- To what extent will mobility benefits depend on connected vehicle (V2V, V2I, and V2P) systems?
- What tradeoffs exist between mobility benefits and other types of benefits (for example: will closer car following present a hazard, or will higher speeds result in greater fuel consumption?)
- What types of enhanced infrastructure (V2I technology, dedicated lanes, etc.) will provide substantial mobility benefits?
- What are the mobility dis-benefits, if any (for example, if an automated vehicle requires large following distances)?
- What are the implications for highway expansion?

We plan to couple the modeling framework with a regional planning model to allow us to capture some of the feedback loops, and to assess impacts of automation on regional mobility, accessibility, and air quality. The framework will also address various levels of fleet penetration (where only some vehicles are equipped with AV technology).

In the area of energy and environment, the framework is designed to support the direct modeling of energy and environmental impacts of specific automation applications (e.g., platooning) at a corridor level. We plan to roll these corridor-level impacts up into national impacts for energy and emissions.

Finally, we anticipate that the framework will provide an assessment of direct economic impacts (costs savings from reduced crashes and improved mobility).

Intended Users

Users of the framework will include anyone who wishes to use quantitative analysis to better understand the impacts of automated vehicle scenarios. Federal and State DOTs may use it to support policy analysis. State DOTs and MPOs may use it for long-range scenario-based planning, where various automation futures are envisioned. OEMs and after-market equipment manufacturers may use it to better understand the potential benefits and design parameters of their applications.

Overarching Vision

The modeling framework is a comprehensive approach for a quantitative assessment of the wide-ranging impacts of various automation scenarios. It is not

- A forecast of what those scenarios might be
- Research on the characteristics of any particular automation application
- A policy prescription

[2] Aspects of a scenario may include, but not be limited to, the type of road, whether vehicle-to-vehicle communications exist, and the market penetration of AVs

Rather, the forecasts of scenarios, and the characteristics of particular automation applications serve as inputs to the framework. The outputs are intended to help inform policy decisions.

The framework has the following characteristics, which will be discussed further in Chapter 4

- It will be designed to facilitate the comparison of multiple scenarios. For example, one scenario might be to compare an adaptive cruise control automation application (Level 1)3 to a no automation (Level 0) status quo. Another might be to compare a driverless car deployment (Level 4) with a much lower level of automation. Scenarios can also be used to address the degree to which vehicles are connected with each other and with the infrastructure.
- It will include a number of submodels to address the various benefit areas.
- It will address multiple time scales, ranging from second-by-second vehicle performance, to multi-year impacts.
- It will use existing models, where possible, to address the various aspects of automation and benefit areas.
- It will be built incrementally, so that some initial results will be available within a reasonable timeframe. Although the first iteration will assume that all vehicles have the same level of automation, subsequent iterations will consider mixed vehicle streams, in order to capture the impacts of varying levels of market penetration.

The submodels include the following:

- **Safety:** Safety modeling primarily deals with the behavior of driver/vehicle/automation system in the seconds leading up to a potential crash. Thus, safety modeling tends to be performed at an extremely fine-grained level of spatial and temporal resolution, with the results being rolled up into national benefits.
- **Vehicle and Regional Mobility:** Vehicle mobility deals with car following, gap acceptance, and other detailed aspects of vehicle performance. Regional mobility is at a less fine-grained spatial and temporal resolution, and deals with the performance of a highway corridor, an intersection, or a region.
- **Energy / Environmental:** A detailed driving cycle (idle time, acceleration, cruise, deceleration) that comes from the mobility modeling is fed into a model that calculates energy consumption and emissions.
- **Transportation System Usage:** Travelers will change their travel patterns in response to changes in mobility (for example, if a road becomes less congested, it may receive more use). This part of the framework captures the traveler responses to changes in mobility and accessibility. As such, it drives most of the feedback. In the longer term, car ownership and shared ride options may change.
- **Accessibility:** Accessibility measures the ability of people to reach desired destinations.
- **Land Use:** Land use addresses the density and mix of development in a particular region
- **Economic Analysis:** Many of the other benefits, including reduced cost of crashes and congestion and improved access to jobs, lead to economic benefits.

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[3] NHTSA (National Highway Traffic Safety Administration, 2013) and SAE (SAE, 2014) have defined levels of automation, ranging from no automation (Level 0), to driver assistance for a single vehicle function (Level 1), to full automation with no driver required (Level 4 for NHTSA, Level 5 for SAE).

Chapter 2 Areas to Be Addressed and Metrics

This section of the report presents the areas to be addressed by the framework (safety, mobility, etc.), and proposes metrics, data sources and modeling approaches for each of these areas.

2.1 Safety

Automated vehicles have the potential to reduce motor vehicle crashes and mitigate the severity of injuries by performing safety-critical driving controls effectively without depending upon driver inputs.

Proposed safety performance measures include the following:

- All motor vehicle crashes
    - Total
    - Per 100,000 population
    - Per 100 million vehicle miles traveled (VMT)
- Injury crashes
    - Total
    - Per 100,000 population
    - Per 100 million VMT
- Fatal crashes
    - Total
    - Per 100,000 population
    - Per 100 million VMT
- Persons injured or killed in motor vehicle crashes, both overall and broken out by subgroups (motorcycle rider, pedestrian, bicycle, truck, bus)
    - Total
    - Per 100,000 population
    - Per 100 million person miles traveled
- Public transit injuries and fatalities
    - Total
    - Per 100,000 unlinked trips
    - Per 100 million person miles traveled (PMT)
- Monetized value of crashes
    - Total
    - Per capita

Intermediate measures include exposure, prevention and fatality ratios. They are discussed in section 4.2.

Because automation may result in both changes in trip making and in vehicle occupancy, a variety of normalizations are necessary to understand the full impacts. Consider the following example (which, for simplicity, includes only private vehicles and fatalities). Even in this simplified example, without public transit, person miles traveled need to be considered because vehicle occupancy might change.

The base condition is an area of 1 million people with 10 billion annual VMT and 13 billion annual person miles traveled. The area experiences 80 fatal crashes each year, with 100 fatalities. In this example, automation is accompanied by substantial vehicle sharing with more personal trip making, so that VMT decreases to 8 billion, while person miles increases to 15 billion. There are 50 fatal crashes, with 80 fatalities. The monetary value of a fatality is assumed to be $9.1 million. Table 1 illustrates the values of various safety measures.

Table 1. Examples of Safety Measures

Measure (all are per year)	Baseline value	Automation value	Improvement
Fatal crashes – total	80	50	38%
Fatal crashes – per 100K population	8	5	38%
Fatal crashes – per 100M VMT	0.800	0.625	22%
Persons killed – total	100	80	20%
Persons killed – per 100K population	10	8	20%
Persons killed – per 100M PMT	0.769	0.533	31%
Monetary value	$910 million	$781 million	20%

2.1.1.1 Data Sources

Data sources include driver, vehicle, and application performance data from controlled tests in driving simulators and test tracks. Additional driver data come from naturalistic driving studies such as the Safety Pilot Model Deployment and the Integrated Vehicle-Based Safety System study.

To understand the target crash characteristics, and to roll up safety impacts to national-level benefits, a number of databases are available.

The National Automotive Sampling system[4] (NASS) includes the General Estimates System (GES) and the Crashworthiness Data System (CDS). GES data come from a national sample of police reported motor vehicle crashes of various levels of severity, ranging from minor to fatal. Approximately 50,000 police accident reports are sampled each year. GES began operation in 1988. In 2014, the most recent information that appeared was from 2012. In 2003, (Najm, Smith, & Campbell, 2003) used data from GES to analyze light vehicle crashes and identify pre-crash scenarios.

The CDS has detailed data on a sample of approximately 5,000 crashes each year, and is used to better understand the crash-performance of passenger cars, light trucks, vans and utility vehicles. As of 2014, data were available from 2004 to 2013.

The Fatality Analysis Reporting System[5] (FARS) contains information on all reported fatal crashes. As of 2014, data were available from 1975 to 2012. Subsets of the FARS include databases for Trucks in Fatal Accidents (TIFA) and Buses in Fatal Accidents (BIFA)

[4] http://www.nhtsa.gov/NASS
[5] http://www.nhtsa.gov/FARS

Special Crash Investigations (SCI) contains extremely detailed information for approximately 100 selected crashes each year.

It is expected that the AV benefits framework will primarily use the GES and FARS data sets.

2.1.2 Past Research on Safety

There are many papers on the potential impacts of specific automation applications on safety, which will be discussed in Chapter 3 This section reviews some of the studies that have applicability to several automation applications.

2.1.2.1 Driver Performance

Numerous simulator-based studies have been undertaken to better understand aspects of driver performance. Furthermore, over the years, traffic engineers have developed empirical rules of thumb (e.g., for reaction time and driver visual acuity) that are used to inform road design.

In 2004, NHTSA and the Virginia Department of Transportation sponsored a 100-Car Naturalistic Driving Study. Drivers were instructed to drive as they naturally would, in an instrumented vehicle. The instrumentation includes sensors of vehicle status, an accelerometer, distance to lead and following vehicles, detection of side conflicts, video monitoring of events in and around the vehicle, and a means to allow drivers to flag incidents. Results of the field experiment were summarized in (Dingus, 2006). More recently, the Second Strategic Highway Research (SHRP2) program has sponsored a larger naturalistic driving study.[6]

Examples of recent work at TFHRC that have looked at driver behavior included an attempt to model drivers as agents (Driver Behavior in Traffic)[7], and a study of the human factors aspects of cooperative adaptive cruise control (Jones, 2013).

The L2L3 project, recently completed, examined driver interaction with level 2 and level 3 automation (Marinik, Bishop, Fitchett, Morgan, Trimble, & Blanco, 2014).

In a review paper, (Banks, Stanton, & Harvey, 2013) discuss how increasing automation may affect the driver's role, and the potential implications for safety.

2.1.2.2 Other Safety Research

In the National Motor Vehicle Crash Causation Survey (NMVCCS) (NHTSA, 2008), NHTSA analyzed the pre-crash events and critical factors for 5,471 passenger-vehicle crashes in the U.S. between 2005 and 2007. Results from this study suggest that human error is the critical reason for 93 percent of crashes. Human errors were categorized into recognition (e.g., inattentive, distracted), decision (e.g., too fast, gap misjudgment), performance (e.g., overcompensation, poor control), and non-performance (e.g., sleepy, ill) errors. In 2014 the Casualty Actuarial Society's Automated Vehicles Task Force[8] re-evaluated the NMVCCS study results in the context of an automated vehicle world (Stienstra, 2014). This re-evaluation found that 49 percent of crashes

[6] http://www.shrp2nds.us/
[7] http://www.fhwa.dot.gov/advancedresearch/pubs/10070/index.cfm
[8] http://www.casualtyactuarialsociety.org/

contain at least one limiting factor that could disable the technology or reduce its effectiveness. Limiting factors were categorized into technology issues (i.e., inclement weather, vehicle deficiencies, and inoperable traffic control devices) and driver behavioral issues (i.e., inebriated and distracted drivers).

In a 2014 report (Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014) that supported the Advanced Notice of Proposed Rulemaking for V2V technology, NHTSA presented the safety impact methodology and its application to V2V technology.

2.2 Mobility

Automated vehicles have the potential to improve mobility on a personal, vehicle, and regional scale.

At the personal scale, fully automated vehicles could create an opportunity to provide independent mobility for travelers of all abilities and ages. There is also potential to improve first-mile last-mile mobility from transit stops. The inability of current transit services to deliver travelers all the way from their origin to their destination is thought to detract some potential riders from using transit instead of a personal vehicle (Levine, Zellner, Shiftan, de Alarcon, & Diffenderfer, 2013). Of course, ease in travel may encourage additional trips that would have otherwise not been taken, potentially leading to greater VMT.

Automated vehicles in a highway scenario could travel more closely to one another if the application allows for more precise lane keeping and/or smaller car following headway than would be safely possible with a human driver. This could keep traffic flowing more smoothly leading to reduced delay and travel time variability. Similarly on an urban arterial, automated vehicles may have applications that allow for a smaller gap acceptance than would a human driver, also leading to improvements in delay and travel time variability. On the other hand, automated vehicles that require larger following distances and more conservative gap acceptance could create mobility dis-benefits.

At the regional scale, car following, lane keeping and gap acceptance applications could bring significant changes in freeway, arterial, or intersection effective capacity.

Measuring these mobility improvements can occur on several levels, ranging from a road segment or intersection, to a corridor, to a region, to the Nation. Proposed measures for each are presented below.

2.2.1.1 Road Segment

Performance of a road segment is important for uninterrupted facilities, such as freeways. Planning models typically make use of freeway capacities measured in vehicles / hour / lane. There is a well-established and measurable relationship between speed and traffic volume on a freeway segment (Figure 1), which could lead to several performance measures that address delay, travel time variability and freeway effective capacity.

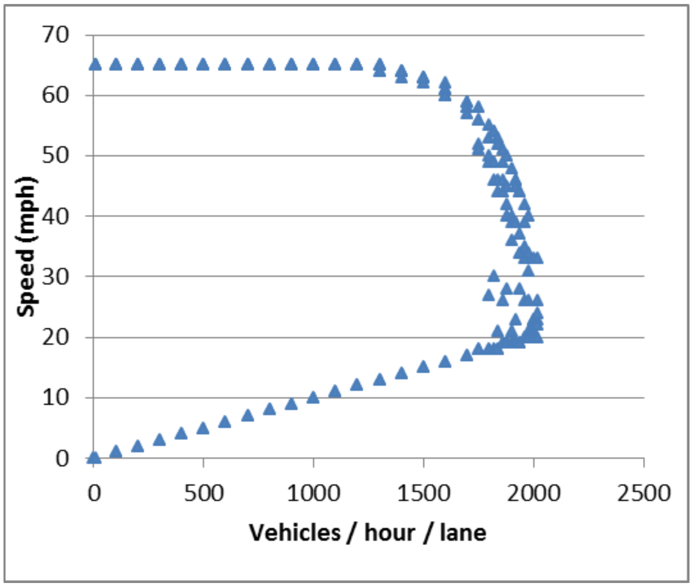

Figure 1. Speed-Flow Diagram for Freeway Traffic (notional) (Source: U.S. DOT)

Measures that could be computed from the data in this diagram include:

- Capacity at 55 mph (approximately 1800 vehicles / hour / lane)
- Maximum capacity (approximately 2000 vehicles / hour / lane)
- Free flow speed (65 mph)
- Median speed (40 mph)
- 5th percentile speed (18 mph) - addresses "worst case" reliability.

To assess the performance of an automation application, one could compute the measures that are based on the Speed-Flow diagram with and without the application. Figure 2, with notional data, shows an example with an imaginary application that provides a rather modest improvement in lane capacity.

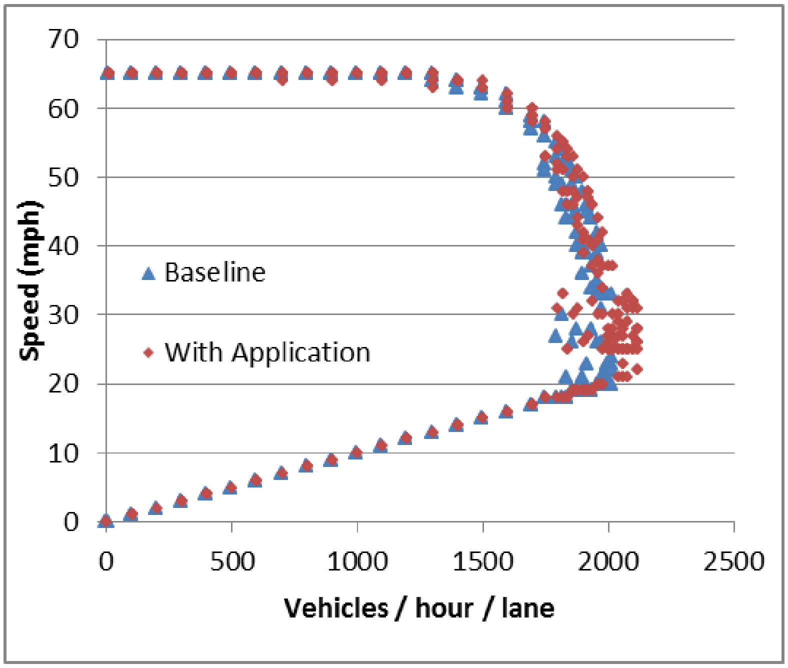

Figure 2. Speed-Flow Diagram for Freeway Traffic Comparing Baseline to Conditions with an Application (notional) (Source: U.S. DOT)

2.2.1.2 Intersection Approach

For interrupted facilities such as urban arterials, the mobility performance of the facility is usually governed by the performance of its signalized intersections. One performance measure would be

- Vehicles / hour through a particular intersection approach, normalized to number of lanes and proportion of green time.

2.2.1.3 Corridor

A corridor may be a section of freeway, or an arterial with a length of at least several miles, and travel times measured in minutes. Measures of mobility would include

- Average travel time (minutes)
- 95th percentile travel time (minutes). This measure addresses travel time reliability.

2.2.1.4 Region

A region may be a section of a city, the area covered by a Metropolitan Planning Organization planning model, or even a State. Mobility measures that easily fall out of a planning model include the following:

- Total trips (used for normalization)
- Total travel distance (used for normalization)
- Total travel time (minutes)
- Average trip duration (minutes)
- Average trip length (miles)
- Average travel speed (MPH).

The mobility measures used by FHWA[9] are also relevant at the regional level. Measures include

- Congested hours per day for limited access highways.[10]
- Travel time index, defined as the ratio of peak period travel time to free-flow travel time.[11]
- Planning time index, a measure of trip time reliability, defined as a ratio of the total time needed to ensure 95 percent on-time arrival as compared to a free-flow travel time.[12]

2.2.1.5 Nation

In addition to the mobility measures mentioned above (travel time index, planning time index) that can be rolled up to a national measure, other mobility measures used by TTI in the Urban Mobility Report (Schrank, Eisele, & Lomax, 2012) include:

- Travel delay (billions of hours)
- Truck congestion cost (billions of 2011 dollars)
- Congestion cost (billions of 2011 dollars)

Other aggregate measures, from the National Household Travel Survey, include

- Person trips
- Person Miles of Travel (PMT)
- Vehicle trips
- Vehicle Miles of Travel (VMT)
- Vehicle Occupancy

2.2.2 Data Sources

Detailed highway and vehicle performance data for selected roads and urban areas is contained in the Research Data Exchange (RDE) (https://www.its-rde.net/). The U.S. DOT Data Capture and Management Program sponsored the development of the RDE to support research using detailed highway, transit and connected vehicle data. The RDE primarily contains archived data, including detailed highway detector data, traffic signal timing, weather, and a sample of Basic Safety Message data from connected vehicles. Data from

[9] See http://www.ops.fhwa.dot.gov/perf_measurement/ucr/documentation.htm.

[10] This is defined as “the average number of hours during specified time periods in which instrumented road sections are congested (speeds less than 45 mph). For this measure, congestion is defined to occur when link speeds are less than 45 mph. This measure is reported for weekdays (6a-10p).”

[11] Defined as: “The free-flow travel time for each road section is the 15th percentile travel time during traditional off-peak times (weekdays between 9a-4p, 7p-10p; weekends between 6a-10p), not to exceed the travel time at the posted speed limit (or 60 mph where the posted speed is unknown). For example, a value of 1.20 means that average peak travel times are 20 percent longer than free-flow travel times. In this report, the AM peak period is 6a-9a and the PM peak period is 4p-7p on non-holiday weekdays. Averages across road sections and time periods are weighted by VMT.”

[12] The planning time index is a measure of trip time reliability. It “is computed for the AM peak period (6a-9a) and the PM peak period (4p-7p) for non-holiday weekdays. For example, a value of 40 percent means that a traveler should budget an additional 8 minute buffer for a 20-minute average peak trip time to ensure 95 percent on-time arrival. The planning time index is computed as the 95th-percentile travel time of the month divided by the free-flow travel time for each road section and time period. The free-flow travel time for each road section is the 15th percentile travel time during traditional off-peak times (weekdays between 9a-4p, 7p-10p; weekends between 6a-10p), not to exceed the travel time at the posted speed limit (or 60 mph where the posted speed is unknown). Averages across road sections and time periods are weighted by VMT.”

the RDE may prove helpful for calibrating baseline models of detailed driver and highway performance. The RDE also points to the types of data that may be available for calibration and validation of models in other regions that are well equipped with highway traffic detectors and other ITS equipment.

The following are examples of resources that could be helpful in providing a baseline of travel times or congestion measures for the model.

FHWA has access to a national data set of average travel times collected by probe vehicles on the national highway system, which can be extracted out to the county level. This data set is called the National Performance Management Research Data Set (NPMRDS), which is available to FHWA under contract with HERE North America, LLC.[13] The sampling rate is every five minutes and indicates whether vehicles are passenger or freight. From this data set, many performance measures can be calculated, including truck mobility, travel time reliability index, and truck daily delay.

Toll tags may also be used to collect congestion data. For example, New York City is using traffic sensors to detect E-ZPass transponders, and using the data to calculate travel times in several locations throughout Manhattan. The sensors were installed to help manage traffic flow in designated areas using active traffic management.[14]

The Texas Transportation Institute (TTI) produces an Annual Urban Mobility Report, which covers a selection of 101 urban areas nationwide. The dataset includes daily vehicle miles traveled for different road classification types, several measures of congestion, delay, travel time, and reliability. The data set is available as a spreadsheet via the TTI website.[15] The methodology for calculating these performance measures may also prove useful in constructing the model, especially with respect to rolling benefits up to the national level.[16] The I-95 Corridor Coalition's Vehicle Probe Project collected traffic data, including vehicle speed, travel time, volume, and origin-destination. The data are available on the I95 Corridor Coalition website.[17]

There have been several attempts globally to run simulations of automated vehicles to estimate impacts on safety, energy efficiency, mobility, and human driver performance. For example, the European Safe Road Trains for the Environment (SARTRE) project, which uses a platooning system, investigated the behavior of a human driver assigned the task of being a following vehicle in a platoon and produced gap acceptance estimates (Larburu, Sanchez, & Rodriguez, 2010).

2.3 Energy/Environment

A detailed vehicle speed profile at the corridor level can serve as the basis for assessing mobility, energy and environmental impacts. Therefore, similar to mobility impacts, energy impacts can reasonably be assessed at corridor, regional, and national levels. Measures include:

- Vehicle energy consumption (BTU,[18] gallons / 100 miles or electric equivalent[19])
- Personal energy consumption (BTU / person-mile and BTU / person)

[13] http://ops.fhwa.dot.gov/Freight/freight_analysis/perform_meas/index.htm#data
[14] http://www.nyclu.org/files/20110209-DraftTechnicalMemo1_sm.pdf
[15] http://mobility.tamu.edu/ums/methodology/
[16] http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-report-2012-appx-a.pdf
[17] http://www.i95coalition.org/projects/vehicle-probe-project/
[18] 3412 BTU = 1 kWh See http://www.aps.org/policy/reports/popa-reports/energy/units.cfm
[19] 1 gallon of gasoline = 33.7 kWh. See http://www.fueleconomy.gov

- Total fossil (gasoline, diesel, CNG, LNG) energy consumption from highway transportation
- Expenditure for fuel

Emissions measures are closely related to energy measures. Measures include

- Tailpipe[20] carbon dioxide (CO_2) emissions
    - Total
    - Per person
    - Per vehicle-mile
- Tailpipe criteria pollutant[21] emissions
    - Total
    - Per person
    - Per vehicle-mile

2.3.1 Detailed Analysis Using MOVES

The U.S. Environmental Protection Agency (EPA) MOVES2014 program can produce the required measures. This program is a modeling system that estimates emissions of criteria pollutants, GHGs, air toxics, and fuel consumption for mobile sources (EPA, 2014). MOVES2014 incorporates Tier 3 emission standards for cars, light-duty trucks, medium-duty passenger vehicles, and some heavy-duty trucks along with the most recent CAFE standards for light-duty vehicles and medium- and heavy-duty trucks. Additionally, MOVES is capable of estimating emissions and fuel consumption for fuel types including gasoline, E-85, diesel, and electric for many vehicles, as well as compressed natural gas (CNG) for transit buses.

MOVES can be run in the national scale, county-specific, or project-level. For the county-specific and national scales, default data within MOVES is utilized when available, while the project-level domain requires the user to input all relevant information. In order to run MOVES at the project-level domain, relevant inputs include vehicle type, meteorology, fuel specifications, and road network data which consists of link length, link grade, traffic volume and composition and link speed (Alam, Ghafghazi, & Hatzopoulou, Traffic Emissions and Air Quality Near Roads in Dense Urban Neighborhood: Using Microscopic Simulation for Evaluating Effects of Vehicle Fleet, Travel Demand, and Road Network Changes, 2014). Link speed can be supplied through three methods: average speed distribution, second-by-second link drive schedules or operating mode distributions. For the average speed approach, the user supplies average speeds by roadway link and MOVES utilizes default drive schedules embedded in the MOVES database. When users supply the second-by-second drive schedules for each roadway link, MOVES applies these drive schedules across the entire fleet associated with roadway link. The operating mode distribution method allows users to provide a different operating mode for each vehicle type on each roadway type. Using both input and default data, MOVES calculates vehicle-specific power (VSP) in order to translate the user inputs into various operating modes to determine emissions rates (Chamberlin, Holmen, Talbot, & Sentoff, 2013). The vehicle-specific power accounts for a vehicle's acceleration, speed, and mass and drag on a roadway with a given grade and rolling resistance. Several studies have reported that acceleration, speed, grade, or the variables that are included in the calculation of VSP have been shown to significantly affect emissions, thus giving credibility to the VSP calculation as an

[20] In assessing automation benefits, it may be necessary to assume that types of fuel used by automated and non-automated vehicles are the same. It is beyond the scope of this project to assess the CO_2 emissions from electricity generation.

[21] Criteria pollutants include ozone, particulate matter, carbon monoxide, nitrogen oxides, sulfur dioxide and lead. See http://www.epa.gov/airquality/urbanair/

effective method of estimating emissions (Yao, Wei, Perugu, & Liu, 2014). Other researchers have also examined the effect of mass on emissions in heavy duty vehicles and transit buses (Boriboonsomsin, Wu, Hao, & Barth, 2015) (Alam, Xu, & Hatzopoulou, An Analysis of Instantaneous Speed Distributions and Emissions for Transit Buses Across and Urban Network, 2015). Studies have shown that when users input either operating mode distribution or second-by-second driving schedules, MOVES gives better estimates of emissions than the average speed distribution input (Alam, Ghafghazi, & Hatzopoulou, Traffic Emissions and Air Quality Near Roads in Dense Urban Neighborhood: Using Microscopic Simulation for Evaluating Effects of Vehicle Fleet, Travel Demand, and Road Network Changes, 2014), (Yao, Wei, Perugu, & Liu, 2014), (Abou-Senna & Radwan, Developing a Microscopic Transportation Emissions Model to Estimate Carbon Dioxide Emissions on Limited-Access Highways, 2014).

Several methodologies have been utilized for linking traffic micro- simulation models (TransModeler, VISSIM, PARAMICS, AIMSUN) to MOVES in a variety of applications including environmental impacts on managed lanes strategies, limited-access highways, slip lane configurations, transit-oriented developments, bus service improvement strategy comparison, emissions at various congestion levels as well as hot-spot analysis (Alam, Ghafghazi, & Hatzopoulou, Traffic Emissions and Air Quality Near Roads in Dense Urban Neighborhood: Using Microscopic Simulation for Evaluating Effects of Vehicle Fleet, Travel Demand, and Road Network Changes, 2014), (Chamberlin, Holmen, Talbot, & Sentoff, 2013), (Abou-Senna & Radwan, Developing a Microscopic Transportation Emissions Model to Estimate Carbon Dioxide Emissions on Limited-Access Highways, 2014), (Abou-Senna & Radwan, Microscopic Assessment of Vehicular Emissions for General Use Lane and Managed Lanes: A Case Study in Orlando, Florida, 2014), (Talbot, Chamberlin, Holmen, & Sentoff, 2014) (Veeregowda, Lin, & Herman, 2015). Multiple analyses have used a more direct linkage between traffic micro-simulation tools and MOVES. (Lin, Chiu, Vallamsunder, & Song, 2011), (Song, Yu, & Zhang, 2012) and (Chamberlin, Choices to Make When Conducting a Hot-Spot Analysis Using MOVES, 2012) have utilized various approaches linking traffic micro-simulation tools to MOVES. The second-by-second driving vehicle operations from a micro-simulation model are valuable in utilizing the MOVES operating mode algorithm for correctly estimating emissions (Abou-Senna & Radwan, Microscopic Assessment of Vehicular Emissions for General Use Lane and Managed Lanes: A Case Study in Orlando, Florida, 2014). However, various studies have cautioned about the need to obtain real-world operational activity data for the microsimulation data because the default parameters do not adequately model appropriate driver behavior, resulting in overestimation of emissions (Alam, Ghafghazi, & Hatzopoulou, Traffic Emissions and Air Quality Near Roads in Dense Urban Neighborhood: Using Microscopic Simulation for Evaluating Effects of Vehicle Fleet, Travel Demand, and Road Network Changes, 2014), (Chamberlin, Holmen, Talbot, & Sentoff, 2013), (Talbot, Chamberlin, Holmen, & Sentoff, 2014). Abou-Senna and Radwan also reported that “emission rates were found to be highly sensitive to the frequent acceleration events that occur at lower speeds,” further emphasizing the need for accurate understanding of driver behavior (Abou-Senna & Radwan, Microscopic Assessment of Vehicular Emissions for General Use Lane and Managed Lanes: A Case Study in Orlando, Florida, 2014). Fontaras et al. also raised the issue that in micro-simulation models and their integration with MOVES, the driver-vehicle system is modeled as a single entity and therefore misses the effects of “steering, gear-changing or brake- and accelerator-pedal control” on fuel consumption and emissions (Fontaras, et al., 2015).

The MOVES analysis will yield the following metrics:

- Tailpipe Carbon Dioxide (CO_2) emissions (total, per capita, per vehicle-mile)
- Tailpipe criteria pollutant emissions including tire wear and brake wear particulates (total, per capita, per vehicle-mile)
- Vehicle energy consumption
- Person energy consumption
- Total fossil energy consumption from highway transportation

2.3.2 Other Energy / Emissions Models

MOVES is the EPA-designated regulatory model utilized for modeling fuel consumption and emissions. For California, the designated regulatory model is the Emissions Factors (EMFAC) model, developed by Caltrans and analyzed by the University of California at Davis. This model utilizes the mobile source emissions inventory maintained by California's EPA Air Resources Board (ARB) to provide emissions or emission rates at the project level for various on-road vehicles, including trucks, buses and passenger cars calculated from vehicle miles traveled, vehicle fleet mix, vehicle age distribution, as well as average speed and drive schedules specific to California (California Environmental Protection Agency Air Resources Board, 2014) (California Environmental Protection Agency, 2011).

Besides MOVES2014 and EMFAC, there are other fuel consumption and emissions models, including Moves Lite, the Comprehensive Modal Emissions Model (CMEM) and VT-Micro model. Moves Lite was developed by researchers at North Carolina State University due to the computationally intensive nature of MOVES, intending to be used with a traffic micro-simulation model but does not require all of the adjustments in MOVES such as temperature variation, fleet mixture and fuel properties. (Liu & Frey, 2013) (Frey & Liu, 2013). CMEM, developed at the University of California, Riverside and tested and validated for a variety of light duty vehicle and light duty trucks, utilizes the same operating mode approach as MOVES but assigns operating modes through the calculation of fuel rate consumption rather than vehicle-specific power (Nam, 2003). Although fuel rate calculations provide a more robust and developed methodology, its complexity requires significant user training to utilize properly (Nam, 2003). The VT-Micro model from Virginia Tech researchers is a statistical model that estimates emissions and fuel consumption using regression models derived from chassis dynamometer and on-road emissions and fuel consumption data (Ahn & Rakha, 2013).

Argonne National Laboratory has developed a tool which is used throughout the different phases of the Model Based Design of the Vehicle Development Process (VDP) called Automonie.[22] Through plug and play architecture, advanced technologies can be tested to determine the emissions and fuel economy impacts.

2.3.3 Measurement of Energy/Emissions at the National Level

The Transportation Energy Data Book (Davis, Diegel, & Boundy, 2013) provides information on energy consumption by transportation mode as well as vehicle production, scrappage and survival rates, and fuel economy broken down by vehicle class. (Chester, Horvath, & Madanat, 2010) presented a life-cycle energy and emission inventory for three U.S. metropolitan regions that considers both vehicle operations and the non-operation (including vehicle manufacturing and roadway maintenance) components of passenger transportation.

The National Renewable Energy Laboratory (NREL) Report on Energy Impacts of Automated Vehicles and others have investigated the potential effects of Automated Vehicles in regard to energy consumption and identifies potential fuel savings (Gonder, 2014), (Fagnant & Kockelman, Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendation for Capitalizing on Self-Driven Vehicles, 2014), (Wu, Boriboonsomsin, Xia, & Barth, 2014). Effects that they considered include:

- Platooning
- Two levels of more efficient driving with smoother starts and stops
- More efficient routing (traffic avoidance)
- Travel by underserved populations (youth, disabled, elderly)

[22] http://www.autonomie.net/overview/index.html

- Faster travel
- More travel (people able to live farther from destinations)
- Lighter vehicles
- Less time looking for parking
- Higher occupancy vehicles – automated car-sharing
- Electrification
- Fewer cold starts
- Less congestion (idling time in traffic).

2.3.4 Past Research on Automation and Energy/Emissions

(Gonder, 2014) found that enabling electrification of vehicles potentially offers the greatest positive energy outcomes because it could significantly decrease fuel consumption. This conversion to electric-powered vehicles has the potential to positively impact the human environment as well by reducing the amount of carbon monoxide, nitrogen oxides, and hydrocarbons in the urban environment, all of which are known to be risks to human health (Parry, Walls, & Harrington, 2006). (Gonder, 2014) also found that faster travel, more travel, and increased demand for travel by previously underserved populations offer the possibility for significant negative energy outcomes. These effects, however, may be balanced at least in part by automated car-sharing or ride-sharing.

Olia et al. performed analysis on connected vehicles impacts and reported that a 30 percent reduction for carbon dioxide emissions can occur in a network composed of 50 percent connected vehicles (Olia, Abdegawad, Adbulhai, & Razavi, 2014). Overall, these studies predict automated vehicles or connected vehicles are expected to experience some reduction of emissions.

2.4 Accessibility

Accessibility is a function of both land use and the transportation network. It measures “the ease of reaching valued destinations” (Owen & Levinson, 2012). Accessibility measures typically have two components: the impedance factor and the destination factor. The impedance factor is related to the journey itself and has a dampening effect on accessibility. The destination factor is related to the characteristics of the destination location (Bhat, Handy, Kockelman, Mahmassani, Chen, & Weston, 2000). However, the impedance factor is more likely to relate to the transportation system.

One direct measure of accessibility is the number of jobs or other desired destinations that can be reached from a household, weighted by the time (or generalized cost) required to reach them. For example, an accessibility measure could be:

$$a = \sum_{c} j_c \exp(-bc)$$

Where
a is the measure of accessibility from a household to various attractions
c is a generalized cost, equal to travel time * value-of-time + out-of-pocket cost
j is the number of attractions (jobs, shopping, etc.) reachable at cost c
b is a weighting factor. (Owen & Levinson, 2012) used 0.08.
For this measure, it is helpful to distinguish between motorists and non-motorists, in order to capture the accessibility benefits of full automation for non-motorists.

Other measures include:

- Total transportation cost for a household (as a percentage of household income).
- Percentage of people within x-minutes of major activity (employment, medical, etc.)
- Average wait for shared vehicle
- Effective system capacity
- Land use mix
- Average commute distance.

There are many different ways to measure accessibility, depending on the mode, user, geographic scale, and perspective. Much of accessibility is dependent on transportation infrastructure and land use, as these elements can greatly affect the distance traveled and/or circuitousness of the path. In the case of modeling accessibility impacts of automated vehicles, these factors would be fixed, unless they were deemed to be a direct result of the presence of automated technology. Accessibility improvements associated with automated vehicles may come from reduced congestion, increased transportation options for non-drivers, and improved first-mile-last-mile connectivity with transit. For the purposes of this framework, we will consider accessibility as part of the regional transportation modeling process.

(Levinson D. M., 2013) measured the number of jobs in the 51 largest U.S. metropolitan areas that are accessible by automobile within certain travel time ranges. He considered geographic locations of homes and jobs, roadway network connectivity, and average traffic speeds to make the estimates.

Another possible source of accessibility data is University of Minnesota Center for Transportation Studies, which is evaluating accessibility changes in the Twin Cities region over time (Litman, 2014).

2.5 Economic Benefits

In addition to the specific benefit areas described above, automated vehicles have the potential to create broader macroeconomic benefits, to the extent that the impacts of automation are large enough to influence labor supply or other determinants of economic growth. One example would be that Level 4 automation (self-driving vehicles) would remove barriers to job access for large numbers of non-drivers, boosting their labor force participation. Among drivers, safety improvements would mean fewer working hours that are lost to crash-related injuries, to congestion and other travel delays, and to the demands of “chauffeuring” children or elderly relatives. Also, when relieved of most or all hands-on driving responsibilities, travelers could spend a portion of their travel time in productive work activities, thereby also increasing labor supply.

Another potential impact, though more difficult to model, is that reduced congestion can increase workers’ effective commuting radius, allowing better matching of jobs to skills and thus greater division of labor and higher output per unit of labor. Self-parking and/or self-repositioning vehicles could also substantially reduce the acreage required for parking facilities, allowing that land to be used for other uses and potentially spurring economic development.

Key metrics would include:

- Gross Domestic Product: total, per capita, and per hour worked
- Total factor productivity / 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.

Data sources to support these metrics are available largely through public statistics, such as GDP estimates from the Bureau of Economic Analysis; Bureau of Labor Statistics data on workforce participation and compensation; and NHTSA figures on the number and severity of motor vehicle crashes. For more detailed metrics – and particularly for sector-specific analysis – these statistics may need to be augmented by information from private economic research services.

Existing research in this area is fairly limited, although there have been some initial efforts to outline the effects of automation on specific sectors of the economy and overall economic activity. (Fagnant, D. and K. Kockelman, Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendations for Capitalizing on Self-Driven Vehicles, Presented at 93rd Annual Meeting of Transportation Research Board, 2014.) Other existing work, addressing the impacts of conventional transportation investments on overall productivity and output, may also be transferable to the case of automation. (Puckett, Lee, Pickrell, Price, Dixon, & Rimmer, 2015).

Chapter 3 Automation Applications

After introducing the NHTSA and SAE levels of automation, this section of the report presents a number of automation applications, along with a summary of recent research on each selected application. It is intended that the initial use of the framework be focused on one or more of these applications.

3.1 Levels of Automation

Both NHTSA (National Highway Traffic Safety Administration, 2013) and SAE (SAE, 2014) have defined levels of automation, ranging from driver assistance for a single vehicle function, to full automation with no driver required. These levels provide a useful shorthand for defining various automation scenarios. However, it is more important to thoroughly understand the capabilities of a particular automation application.

At levels 0 – 3, the NHTSA and SAE definitions are essentially the same. NHTSA uses level 4 for full automation, while SAE splits full automation between level 4 and level 5.

SAE describes Level 0 as “the full-time performance by the human driver of all aspects of the dynamic driving task, even when enhanced by warning or intervention systems.” NHTSA describes Level 0 as “The driver is in complete and sole control of the primary vehicle controls – brake, steering, throttle, and motive power – at all times.”

SAE describes Level 1 as the “driving mode-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the human driver perform all remaining aspects of the dynamic driving task.” NHTSA describes Level 1, Function-Specific Automation as, “Automation at this level involves one or more specific control functions. Examples include electronic stability control or pre-charged brakes, where the vehicle automatically assists with braking to enable the driver to regain control of the vehicle or stop faster than possible by acting alone.”

SAE describes Level 2 as the “driving mode-specific execution by a driver assistance system of both steering and acceleration/deceleration, using information about the driving environment and with the expectation that the human driver perform all remaining aspects of the dynamic driving task.” NHTSA describes Level 2, Combined Function Automation as “This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering.”

SAE describes Level 3 as “the driving mode-specific performance by an automated driving system of all aspects of the dynamic driving task with the expectation that the human driver will respond appropriately to a request to intervene.” NHTSA describes Level 3, Limited Self-Driving Automation, as “Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time. The Google car is an example of limited self-driving automation.”

SAE describes Level 4 as "the driving mode-specific performance by an automated driving system of all aspects of the dynamic driving task, even if a human driver does not respond appropriately to a request to intervene." NHTSA describes Level 4, Full Self-Driving Automation, as "The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Such a design anticipates that the driver will provide destination or navigation input, but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles."

SAE describes Level 5 as "the full-time performance by an automated driving system of all aspects of the dynamic driving task under all roadway and environmental conditions that can be managed by a human driver."

The primary difference between the NHTSA and SAE levels is that SAE makes the distinction between fully automated driving in all driving modes[23] (level 5), and fully automated driving in selected driving modes (level 4). Since this distinction is important, the remainder of this report will use SAE levels of automation. The difference between level 3 and level 4 is that in level 4, the automation system has the capability to restore the vehicle to a minimal risk condition, even if the human driver fails to respond to a request to intervene. Table 2, adapted from (SAE, 2014), presents the human versus system responsibilities at each level of automation.

Table 2. Levels of Automation, adapted from (Shladover & Lappin, 2015)

Level	Example Systems	Driver Roles
1	Adaptive Cruise Control or Lane Keeping Assistance	Must control remaining driving functions and monitor driving environment
2	Adaptive Cruise Control and Lane Keeping Assistance, Traffic Jam Assist	Must monitor driving environment (system alerts driver to ensure engagement)
3	Traffic jam pilot, automated parking	May engage in non-driving activities (except sleeping), but be prepared to intervene when needed
4	Highway driving pilot, closed campus driverless shuttle, driverless valet in parking garage	May sleep; system can revert to minimum risk condition if needed
5	Automated taxi for non-drivers (even children), Car-share repositioning system	No driver needed

3.2 Choice of Sample Applications

Possible applications for automation were mostly taken from Appendix 4 of the 2014 report, "Development of a Multimodal Program Plan for Automated Vehicles" (Volpe Center, 2014). They include:

- Collision avoidance applications, including

[23] SAE defines driving mode as "A type of *driving* scenario with characteristic *dynamic driving task* requirements (e.g., expressway merging, high speed cruising, low speed traffic jam, etc.)."

    - Forward Collision avoidance
    - Lane departure warning/avoidance
    - Blind spot warning
    - Backup assistance
- Cooperative Adaptive Cruise Control (CACC)
- Speed Harmonization
- Platooning
- Intersection Management
- Lane Change, Merge and Demerge
- Lane Weaving
- First and Last Mile Mobility
- Automated Paratransit
- Transit Lane Assist
- Transit Precision Docking
- Automated Yard Operations
- Full Automation (driverless cars)

Criteria for selection included the following:

- The applications are of substantial interest to U.S. DOT, as indicated by research activity.
- The combined applications cover the full range of vehicle automation, from Level 1 to Level 4, and provide benefits in all of the areas of safety, mobility, accessibility, energy, and the environment. The framework does not preclude level 5 analysis; however, applications were selected on the basis that they are reasonably close to deployment.
- At least some of the applications are defined well enough so that a quantitative estimation of benefits can be made.

Based on the criteria listed above the following automation applications were selected:

- Collision avoidance
- Traffic jam assistance
- Cooperative Adaptive Cruise Control (CACC)
- Platooning
- Full automation in a controlled environment

3.3 Collision Avoidance

Collision warning applications (Level 0) are those safety applications that sense other vehicles and objects. Applications include forward collision warning, backing collision warning, blind-spot monitoring, land departure warning, pedestrian detection, adaptive headlights, and park assist. (Consumer Reports, 2014) (Insurance Institute of Highway Safety, 2012) (Moore & Zuby, Collision Avoidance Features: Initial Results, 2013) (Jeong & Oh, 2015)

Collision avoidance applications are those Level 1/2 safety applications that have an automation component (e.g., automatic braking). Applications include forward collision warning with auto-braking, and backing collision warning with auto-braking.

These applications were selected because

- They exist to some extent now, and therefore can be well defined.

- They provide obvious potential safety benefits, and attempts have already been made to quantify these benefits.

The Insurance Institute for Highway Safety (IIHS) has reviewed a number of vehicles with auto-braking systems for forward collisions (Insurance Institute for Highway Safety, 2014), (Moore & Zuby, Collision Avoidance Features: Initial Results, 2013). During the 23rd Enhanced Safety of Vehicle Conference, (Hulshof, Knight, Edwards, Avery, & Grover, 2013), (Chauvel, Page, Fildes, & Lahausse, 2013) and (Schittenhelm, 2013) presented findings for automated braking systems.

(Anderson, Doecke, Mackenzie, Ponte, Paine, & Paine, 2012) used 10 years of crash data from New South Wales (Australia) to develop crash mitigation estimates and a cost / benefit analysis of forward collision avoidance technology. This study predicted significant crash reductions with forward crash avoidance technology (FCAT) systems, but found that the benefit-cost ratio (using current costs of FCAT systems) for passenger vehicles was often less than 1. However, heavy vehicle benefit-cost ratios were much higher (between 2.7 and 9.8).

The effect on drivers of forward collision warning (FCW) alarms was presented in (Fitch, et al., 2008). Their simulation-based estimate determined that a nationwide deployment of FCW in heavy vehicles could reduce the number of rear-end crashes by 21 percent.

In research sponsored by the Federal Motor Carrier Safety Administration, (Murray, Shackelford, & Houser, 2009) investigated the benefits and costs of FCW for the trucking industry. They found that the FCW systems will help to prevent rear-end crashes on combination and single-unit trucks, and that motor carriers purchasing the technology will likely see a positive return on investment.

At this point, there are no examples in the literature of modeling the impacts of collision avoidance on mobility on the corridor or regional level. However, two studies assumed that CACC or adaptive cruise control (ACC) will necessarily accompany collision avoidance in vehicles, and thus work together to improve both safety and mobility (Jeong & Oh, 2015) (Olia, Abdelgawad, Abdulhai, & Razavi, 2015). One study suggested that the recent advances in V2V communication and low latency of dedicated short-range communication (DSRC) could help decrease brake actuation delay and therefore achieve safe platooning with smaller gaps (Olia, Abdelgawad, Abdulhai, & Razavi, 2015). Another study used a range of freeway level-of-service conditions and market penetration rates of automated vehicles to determine the effect on vehicle delay (Jeong & Oh, 2015). They assumed a system called Active Vehicle Safety System (AVSS)—which includes automated emergency braking, ACC, and blind spot detection—was installed in various percentages of the fleet. They used microsimulation data with VISSIM + COM-interface to simulate the controlled vehicle maneuvering using the integrated AVSS algorithm. They also used the surrogate safety assessment model (SSAM) by FHWA, which combines microscopic simulation models and automated conflict analysis to qualify the potential of a crash occurrence. In non-incident traffic conditions, they found the following results:

- Average delay increased when traffic conditions became congested from LOS A to LOS E.
- Vehicle delays reduced by 18.3 - 55.5 percent when there was 100 percent market penetration of AVSS.
- AVSS was most effective at maximizing speed under LOS D.

In incident traffic conditions, simulated by assuming a crash at a pre-identified hazard, which blocked one lane for 25 minutes, they found the following results:

- Vehicle delays reduced by 43.9 percent when there was 100 percent market penetration.
- Shock wave caused by the incident was largely dissipated when there was 100 percent market penetration.

These results are promising and suggest that, when used with ACC or CACC, FCA can help to improve mobility. This being said, it will likely be necessary to model the two of these applications together, as well as ACC/CACC on its own, and to estimate mobility impacts of FCA by comparing the results to each other. Extended mobility benefits of FCA could be modeled by determining the average delay for automobile collisions and subtracting the delay saved by avoiding collision.

3.4 Traffic Jam Assistance

Traffic Jam Assist is a feature included in a handful of current vehicle models. It performs car-following (i.e., longitudinal control) and lane keeping (i.e., lateral control) on highways at slow speeds. It supports the driver with monotonous driving in traffic jams on highways at speeds of up to 60 km/h (~ 37 mph). This function follows a lead vehicle at a safe distance and keeps the host vehicle in the center of the lane. The driver can only activate the function if slow-moving vehicles are detected in front. The driver has to monitor the system constantly and has to intervene if required (e.g., if the vehicle is going to exit the highway at an exit or interchange, a vehicle needs to merge into traffic, or the traffic jam situation ends). It is designed to minimize driver fatigue in stop-and-go conditions and reduce the number of accidents caused by inattentive drivers (TRW, 2013). This application was selected because:

- It exists now,[24] and therefore can be well defined.
- It provides an example of level 2 automation, with both longitudinal and lateral control, but the driver is still expected to be closely engaged with vehicle operation.

This application has been demonstrated by a number of auto-makers such as BMW, Audi, and Ford. The early European project (Highly Automated Vehicles for Intelligent Transport (HAVEit): The Future of Driving, 2009) included a traffic jam assistance component. The BMW Traffic Jam Assistant is an example of a fully functional application. It controls the speed of the car and distance to the car ahead in dense traffic on motorways at speeds of up to 60 km/h, and takes over steering while in the traffic jam.[25] The Mercedes Distronic Plus system only controls longitudinal movements by adapting the speed of the vehicle to the flow of traffic ahead, slowing or braking to a full stop as necessary. When traffic moves, the driver can resume with a tap, or, if the stop is less than 1s, the vehicle will automatically resume (Marinik, Bishop, Fitchett, Morgan, Trimble, & Blanco, 2014). A system developed by Bosch works similarly. If it detects dense traffic, the driver can activate the application by pressing a button, which will cause the vehicle to automatically follow the vehicle in front.[26] Audi and Ford have also developed Traffic Jam Assist systems.

To date, there are no available studies in literature that have attempted to model mobility impacts associated with Traffic Jam Assist; however, Ford Motor Company has performed their own traffic simulations, and have reported that Traffic Jam Assist combined with ACC can reduce travel times by 37.5 percent and delays by 20 percent (Carty, 2012). These benefits are assumed to be the result of a reduction in the "shockwave" phenomena and overall improvement in the stability of traffic jams.

[24] An example is the BMW X5.
[25] http://www.bmw.com/com/en/newvehicles/x/x5/2013/showroom/driver_assistance/traffic_jam_assistant.html
[26] http://www.bosch-mobility-solutions.com/en/de/driving_comfort/driving_comfort_systems_for_passenger_cars_1/driver_assistance_systems_4/driver_assistance_systems_5.html

3.5 Cooperative Adaptive Cruise Control

CACC is defined as a system that combines the automated control of vehicle acceleration and braking with wireless communication with either other vehicles (V2V), or the transportation infrastructure (V2I). CACC is an advancement upon the existing commercially available ACC systems, which uses sensors and cameras to maintain a defined constant time gap from a lead vehicle. CACC assists drivers by automatically setting and adjusting their vehicle's speed and in congested conditions by allowing them to follow other vehicles and respond to routine traffic disturbances such as cut-ins by other drivers. In the absence of lateral control, it is a Level 1 application.

CACC was selected because

- It is an active area of research, with field demonstrations. For example, Turner Fairbank Highway Research Center (TFHRC) currently has a project with the Collision Avoidance Metrics Partnership (CAMP), a consortium of automakers, to examine CACC, both as a paper study on deployment issues and a small-scale demonstration with CACC-equipped vehicles.
- It is expected to provide mobility, energy, and environmental benefits. It may provide safety benefits by avoiding near-crash situations with forward collisions.

While there have been a number of studies on the mobility of impacts of ACC systems, the findings from these studies are inconsistent, varying from positive to negative highway capacity improvement (Zwaneveld & van Arem, 1997). The underlying reason that there is inconsistency among the findings is because researchers have proposed various car-following gap-distance methodologies, many of which are only theoretical (Shladover, Nowakowski, Lu, & Ferlis, 2015). When analyses are performed using constant distance gap methods, which are optimized for mobility, the findings produce positive benefits, which is a truism of sorts. However, when researchers employ the constant time gap distance following approach that more closely resemble what exists in today's ACC systems, the mobility benefits are either neutral or negative. In contrast, we have not observed any studies on the mobility benefits of CACC that have not reported positive benefits.

Some 10 years ago, (Mauch & Cassidy, 2004) examined oscillations within queues of freeway traffic, finding that kinematic wave theory could describe the propagation of the oscillations. This work is relevant because an assessment of the impact of CACC on freeway traffic requires an understanding of car-following behavior, both by humans and by automated systems, and how that behavior translates to traffic flow. (Mehmood, Saccomanno, & Hellinga, 2002) provide a summary of the most important car-following models, along with their formulation and limitations. (Olstam & Tapani, 2004) (Al-Jameel, 2010) and (Kanagaraj, Asaithambi, Kumar, Srinivasan, & Sivanandan, 2013) test and compare various car following models. (Duncan, 1998) describes key components of the Paramics car-following and lane-changing model.

(Naus, Vugts, Ploeg, van de Molendraft, & Steinbuch, 2009) provide simulation results of a CACC system operating in traffic on a simple circular network, finding that CACC promises significant advantages for traffic flow and fuel economy. (Baur, Park, Lee, Jaehyun, & Fullerton, 2014) examine the effect of the message reception probability on the performance of a CACC system.

In Japan, a project is now underway to use CACC coupled with V2I and V2V communications to encourage smoother traffic flow at "sags" (valleys) on expressways, where a downgrade is followed by an upgrade at which vehicles often reduce speed. V2V communication is likely a necessary component of CACC for optimal performance through minimized separation distances and platoon stability (McGurrin & Asare, 2014).
In research sponsored by FHWA, (Jones, 2013) examined CACC with a special focus on its human factors aspects of CACC. The report presented a number of research scenarios for future exploration including

- Willingness to use CACC, as a function of traffic, road configuration, time gaps and system reliability.
- Driver workload, situational awareness and distraction.
- Platoon entry / exit.
- Arterial intersections.
- Carryover effects to driver behavior under manual control (where a closer following distance may not be safe).
- Following vehicle gap comfort (comfort-level of the lead driver with a close following vehicle using CACC).

TFHRC continues to research CACC. They currently have a project with the CAMP, a consortium of auto makers, to examine CACC, both as a paper study on deployment issues and a small-scale demonstration with CACC-equipped vehicles.

The two primary benefits that CACC systems offer over conventional ACC systems with respect to mobility are its ability to enable vehicle platooning and it allows vehicles to safely follow a lead vehicle with a smaller following gap. While platooning will be discussed in further detail in a subsequent section, it is worth noting that the V2V communication of CACC systems is necessary to permit platooning. Experimental CACC systems have been studied in real traffic situations, and have demonstrated the ability to reduce following gap relative to ACC systems from 1.1s to 0.6s (Milanés, 2014). CACC systems can permit this smaller following gap because the lead vehicle is providing “real-time” velocity data which can be processed by the following car on a millisecond time scale as opposed to the ACC system which has a response latency of approximately 1.5s to the lead vehicle (Shladover, Nowakowski, Lu, & Ferlis, 2015). Researchers have found that by reducing the following gap, lane capacity of a highway increases (Shladover, Su, & Lu, 2012), thereby increasing mobility.

In addition to V2V communication, CACC can also take advantage of V2I communications. The two scenarios often invoked to describe the mobility benefits of V2I are the ability to improve coordinated acceleration (from, say, a traffic signal) and the ability to use variable speed limits on highways to maintain throughput at physical bottlenecks.

Microscopic traffic simulation can be used to evaluate the benefits of CACC. In addition to the general assumptions/variables that need to be considered for simulation of automated vehicles such as system programming and performance, market penetration, level of service (LOS), road characteristics, etc., to fully elucidate the potential benefits of CACC, variables that are likely to have a large impact on the analysis of CACC vehicles include:

- V2V, V2I, or V2V + V2I,
- Latency and nature of information transmitted through V2V/V2I communications,
- Mixed lane traffic vs. special purpose/dedicated lanes,
- Gap regulation strategy (e.g., constant distance gap vs. constant time gap).

To distinguish between CACC and platooning, it is assumed that CACC uses vehicle headways similar to those seen today in manual driving (in other words, the mobility benefit comes from reduction of shock waves, not from closer car following), and there are no aerodynamic benefits. Platooning, on the other hand, offers closer car following, and may provide aerodynamic benefits, especially for trucks and buses.

3.6 Platooning

Platooning (truck/bus) uses CACC in a series of heavy vehicles to safely allow short headways at highway speeds to obtain mobility and fuel efficiency benefits. The Close-Headway Platooning function controls the longitudinal and lateral dynamic aspects of the vehicle on highways at all speeds, including entering and leaving the platoon. Platooning enables short-time headways between vehicles in a convoy on a highway, thus reducing fuel consumption by slipstream driving and increasing lane capacities. Platoon members might be passenger cars and/or trucks. The driver of a following vehicle in the platoon is allowed to divert his/her attention from the driving task in the specific scenario of a platoon on a highway. He/she must be in the position to resume control with an increased lead time if a takeover request from the system occurs. It is a level 2 (both longitudinal and lateral control) application.

Platooning was selected because

- It is an active area of research, including field demonstrations both in the U.S. and abroad.
- It is expected to provide mobility, energy, and environmental benefits. The ability to reduce truck air resistance via closer vehicle spacing provides a clear energy and environmental benefit.

Between 2008 and 2012, Japan's Ministry of Economy, Trade, and Industry (METI) carried out a major research project and demonstration of CACC and fully autonomous truck platoons. The primary motivation for the project was to prove the feasibility of automated truck platoons with close following distances, and the potential for resulting GHG reductions.

In an article on the SAE website (Ashley, 2013) reported on the previously mentioned truck platooning research in Japan, the European Safe Road Trains for the Environment (SARTRE) project, and the Partners for Advanced Transit and Highways (PATH) program at University of California, Berkeley. In these tests of heavy trucks at highway speeds, fuel savings for the lead vehicles ranged from 4 to 10 percent and for the following vehicle 5 to 16 percent.

In 2013 (Bjelkeflo, 2013) presented Volvo's view of vehicle automation, including a discussion of their platooning work. More recently, (Zhang, Misener, Chan, Zhou, & Li, 2014) proposed a progressive deployment framework for the automation of commercial vehicle operations.

In Europe, the Cooperative Mobility Solution for Supervised Platooning (COMPANION)[27] project started in late 2013. This three-year research project seeks to identify how the platooning concept may become operational in daily truck transport operations.

In 2014, the FHWA Exploratory Research Program and Caltrans funded a project to explore concept alternatives for truck platooning using CACC. This work will build on past research by California PATH and Volvo to define operational concepts for truck platooning, and prepare for simulation experiments and on-road demonstrations. A second project, led by Auburn University in partnership with Peloton, American Transportation Research Institute (ATRI), Meritor-Wabco and Peterbilt, will demonstrate driver-assistive truck platooning on a highway in Alabama.

[27] http://www.companion-project.eu/

3.7 Full Automation in a Controlled Environment

Although widespread deployment of level 3 and level 4/5 automation for general use is some time in the future, a medium-term possibility is to provide driverless, fully automated vehicles in a controlled environment. A "controlled environment" could have a number of meanings:

1. A vehicle running on a single dedicated guideway with a limited number of designated stops. This type of automation has been in use for many years, especially when one considers automatic elevators.
2. A vehicle running on a fixed network of dedicated guideways, with the ability to skip stops. This is personal rapid transit, which again has a long history.
3. A vehicle running on roads, which may have some limited mixing with other vehicles and pedestrians. For example, this could be a low-speed first mile / last-mile service between a transit station and some final destinations.

For this project, the third type of "controlled environment" is envisioned.

Full automation in a controlled environment was selected because

- It is an example of level 4 automation.
- It provides significant accessibility benefits to non-motorists.
- Some controlled environment field tests are underway; they may provide insights into the infrastructure needed to support level-4 automation.

To achieve full automation a vehicle must be capable of four interdependent functions: navigation, situational analysis, motion planning, and trajectory control. Navigation essentially refers to route planning, which is currently handled by global positioning system (GPS) technology in today's vehicles. GPS and V2V/V2I functions could work together to support a traveler information system that allows the vehicle to avoid certain situations (e.g., road closure, traffic jam, etc.) and reroute. Situational analysis refers to a vehicle's awareness of its surroundings and ability to process the relevant objects and their movements. This can be done with video cameras installed on vehicles and GPS markers embedded in infrastructure. However, video technology is dependent on weather conditions. Other options include radar or ultrasonic sensors and LIDAR (light detection and ranging), which are not weather-dependent. Motion sensing refers to a vehicle's ability to monitor its own movements. Sensors are used to ensure that the vehicle is moving in the direction indicated by the navigation system and that the vehicle moves in a way that avoids collision with object detected by the situational analysis system. Finally, trajectory control is essentially a vehicle's ability to react to the input from the other three systems. The vehicle will adjust its speed and direction while maintaining stability (DHL Trend Research, 2014).

Although widespread deployment of level 4 automation for general use is some time in the future, the prospect has captured popular attention. It is likely that the first commercially available fully automated vehicles will function in a limited environment, only on certain roads and with certain vehicles at low speeds. This type of system would allow for reversing back to manual control in the event that the vehicle leaves the automated environment or receives a request from a human driver. In the event of a safety issue that the automation cannot handle, the vehicle may request the driver to assume control. Driver reengagement can be an issue in this situation, as the driver might not be able to respond quickly enough (Anderson, Kalra, Stanley, Sorensen, Samaras, & Oluwatola, 2014).

When considering full automation, it is important to distinguish between automated vehicles that are cooperative versus autonomous. Autonomous automated vehicles act independent of their infrastructure, with self-contained automation, such as longitudinal control, lateral control, and routing, without assistance from other vehicle and infrastructure communication. Cooperative automated vehicles would be connected wirelessly with other vehicles, infrastructure, or the Internet, directly via mobile devices. Cooperative automation would allow at low latency for vehicle-to-vehicle platooning, and intersection collision avoidance, as well as sharing congesting and routing information at high latency (Olia, Abdelgawad, Abdulhai, & Razavi, 2015).

The mobility benefits of full automation in a controlled, cooperative environment may very well be different than in a controlled, autonomous environment. In an autonomous environment, driverless cars would operate without communication to other vehicles or infrastructure, thus limiting the potential benefits of platooning, traffic flow management, as well as safety and efficiency, which result from connected communication between automated cars (Parent, 2013). Full automation in an autonomous environment presents uncertainty for many benefits, such as safety and mobility, since there are factors out of the driverless vehicle's control that could impact its performance.

3.7.1 Past Work

In 2004, the Defense Advanced Research Projects Agency (DARPA) offered a $1 million prize to the team whose self-driving vehicle could complete a 142-mile desert course within 10 hours.[28] None of the 15 vehicles finished the course. The following year, a second challenge was held. This time, 5 vehicles completed the course. The Stanford University entry finished first and won the $2 million prize. In 2007, DARPA conducted an urban driving challenge in a staged city environment. Six of 11 teams successfully completed the course, with the Carnegie Mellon entry placing first.

Later, several members of the winning Stanford team joined Google and developed a self-driving vehicle which has been tested on public roads in a number of states. At this point, the Google car depends on a highly precise and detailed map of the road that it is using. A number of universities, including Carnegie Mellon, have also developed self-driving vehicles which have been tested on public roads.[29]

The European CityMobil[30] project ran from 2006 to 2011, and included two demonstrations of self-driving vehicles, operating on special guideways. A personal rapid transit system (ULTra) at London Heathrow Airport is now operational,[31] as is a guided bus / tramway system in Castellón, Spain, where vehicle operation is automated on part of the route. (Alessandrini & Stam, 2014) presented an evaluation of the four automated transport systems, Personal Rapid Transit, CyberCars, High Tech Buses and Dual Mode Vehicles, used in the CityMobil project. A follow-on project, CityMobil2,[32] is now underway.

Volvo, in conjunction with the Swedish Transport Administration, the Swedish Transport Agency, Lindholmen Science Park, and the City of Gothenburg, has initiated a 100-car pilot project, which will feature level 3 self-driving (with a driver present) on selected roads in Gothenburg, as well as automated parking (Eugensson, 2014).

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[28] http://www.darpa.mil/NewsEvents/Releases/2014/03/13.aspx
[29] http://www.washingtonpost.com/local/trafficandcommuting/driverless-vehicles-even-in-dc-streets-an-autonomous-car-takes-a-capitol-test-run/2014/08/25/6d26baa8-06a4-11e4-8a6a-19355c7e870a_story.html
[30] http://www.citymobil-project.eu/
[31] Automated vehicles operating on dedicated guideways have a long history. (Furman, Fabian, Ellis, Muller, & Swenson, 2014) presents a review of automated transit networks (fully automated vehicles on exclusive grade-separated guideways providing on-demand service).
[32] http://www.citymobil2.eu/en/

In Japan, research is underway to develop a roadmap (2013 – 2030) for at least limited automated driving by 2020, via a gradual progression from single lane, through lane changes and merging, to all expressways, including optimization to reduce congestion.

Military and industry have seen the use of fully automated vehicles. The U.S. military has worked with defense contractor Lockheed Martin to test convoys of automated off-road trucks in Fort Hood, Texas. A German manufacturer, Fendt, has developed a team of two connected tractors, one of which is driverless and led by the other, improving the productivity and efficiency of agriculture operations (DHL Trend Research, 2014).

3.7.1.1 First Mile / Last Mile Services

Automated vehicles create an opportunity to improve first-mile/last-mile mobility for travelers with and without disabilities. The inability of current transit services to deliver travelers all the way from their origin to their destination is thought to detract some potential riders from using transit instead of a personal vehicle.[33] However, if transit agencies or some other entity were able to make automated vehicles available to the public on a "per ride" basis, much like a taxi, this would offer travelers the benefits of a personal vehicle (privacy, point-to-point and on-demand travel) without the cost associated with vehicle ownership (Polzin, 2013). The elimination of labor costs for the transportation supplier would make this type of transportation competitive and financially self-sustaining. Important features would have to include the ability to accommodate wheelchairs, strollers, and scooters. The objective is to create a small personal mobility vehicle which transports one or more travelers in the neighborhood (sidewalks, city streets, not freeways) to the main public transportation or other hubs.

The National University of Singapore tested a controlled environment autonomous vehicle of this kind on its campus (Chong, et al., 2011) . The vehicle was a golf cart mounted with sensors. Wheel encoders and an onboard inertial navigation system provide data that is used to estimate location. A webcam is used to provide visual feedback and perform video processing. Software modules provide the following capabilities: perception, mapping and prediction, localization, and planning and controlling. The team identified three main challenges: localization, pedestrian detection, and limited onboard sensing capability. In terms of localization, GPS-based localizations may experience severe interference in the presence of tall buildings; in such locations, odometry-based approaches were shown to perform slightly better. For pedestrian detection, cameras are effective but require ambient light and a fair amount of computation. Lasers, while more reliable in varying condition have trouble disambiguating different objects. Finally, sensing technology may not accurately detect oncoming vehicles at intersections due to limited sensing coverage or environmental obstructions.

(Juster & Schonfeld, 2014) compare the trip times for automated guideway transit (e.g., an airport people-mover operating on a fixed route with fixed stops) and personal rapid transit.

3.7.1.2 Automated Shared Ride Services

Similar to first-mile/last-mile service, a fleet of shared mobility vehicles that service an entire urban area can lead to substantive efficiency gains for the individual and society as a whole (Mitchell, W.J., Borroni-Bird, & Burns, 2010). (Spieser, Treleaven, Zhang, Frazzoli, Morton, & Pavone, 2014) suggest that an entire urban area can have its personal mobility needs met by fleet of shared vehicles that is one third of the size of the current personal vehicle fleet.

[33] FHWA (2014) Innovative Neighborhood Transit – Assessing the Demand for an Automated Community Shuttle Service

Car-sharing services today are growing in popularity, but one-way rentals are not often available. If one-way service is an option, then car availability is usually a problem as cars tend to cluster near destinations. Driverless cars that are shared could provide a level of independent mobility similar to the personal vehicle while providing the environmental sustainability of public transportation.

The Spieser study suggests that there are two considerations with respect to fleet sizing:

- Minimum fleet sizing: A fleet of vehicles will stabilize the workload when it can cover distance at least as quickly on average as the rate at which service distance accumulates. This approach helps determine if a fleet is large enough.
- Performance-driven fleet sizing: This approach determines how a fleet size impacts the user experience (e.g., vehicle availability or wait time) and how many vehicles are necessary to ensure that the quality of service provided to the customer is no less than a given threshold.

3.7.2 Challenges with Full Automation

Many challenges and barriers to implementation are related to the very large number of possible scenarios that the vehicle must be able to respond to, including the full range of other vehicles' maneuvers; pedestrians and bicyclists who have a comparatively broader range of behaviors on the roadway compared to motorists; animals entering the roadway; debris; work sites; inclement weather conditions; and poor lighting.

Another challenge with full automation is when the vehicle faces a scenario to which it is unable to respond. In these situations, control may need to be ceded to the human operator. In order for the driver to be able to react to the situation appropriately, he/she must have enough time to restore situational awareness. The challenge lies in ensuring that the automation system can predict these types of scenarios in time to provide the driver with the opportunity to reorient his or her self. It is possible that with full automation, drivers will be enticed to pay very little attention to the road during normal operation. One study (Carsten, Lai, Barnard, Jamson, & Natasha, 2012) found that engagement in the non-driving tasks increased from manual to semi-automated driving and increased further with highly automated driving. There were substantial differences in attention to the road and traffic between the two types of semi-automated driving.

An important consideration regarding full automation is the implication of this technology on vehicle ownership, and thus fleet size. There is potential for the average person to maintain personal vehicle ownership. In the event that vehicles can travel without a human driver present, those who own personal vehicles may be tempted to send them out to run errands while they are unmanned. In this scenario, AVs may take a lot more trips than is efficient, many without any passengers, thus increasing VMT. At the other end of the spectrum is a fleet of mostly (or completely) shared vehicles. These vehicles could provide 24/7 on-demand access in any number of varieties of vehicles. Travel could be very efficient in this scenario and the fleet size would be much smaller than in the former. If rides as well as vehicles are shared, there could be a reduction in VMT. These scenarios are discussed at greater length in (Chase, 2014).

3.8 Using the Framework for Other Automation Applications

The applications that were considered in the development of this framework span a broad range of levels of automation and potential areas of benefit. To model a new application, the modeler first needs to thoroughly understand the likely impacts of the application. Is the application designed to avoid head-on collisions, sideswipes, rear-end collisions? Is it designed to enable closer-car following on freeways, improved performance of unsignalized intersections, improved performance of signalized intersections? With this understanding, the appropriate models can then be borrowed, adapted from the models for a similar application, or constructed.

Chapter 4 Description of the Framework

4.1 General Approach: Submodels and Scenarios

The framework has the following characteristics, which will be discussed further in this section:

1. It will be designed to facilitate the comparison of multiple scenarios. For example, one scenario might be to compare an ACC automation application (Level 1) to a no-automation (Level 0) status quo. Another might be to compare a driverless car deployment (Level 4) with a much lower level of automation. Scenarios can also be used to address the degree to which vehicles are connected with each other and with the infrastructure.
2. It will include a number of submodels (Figure 3) to address the various benefit areas.
3. It will address multiple time scales, ranging from second-by-second vehicle performance, to multi-year impacts.
4. It will use existing models, where possible, to address the various aspects of automation and benefit areas.
5. It will be built incrementally, so that some initial results will be available within a reasonable timeframe. Although the first iteration will assume that all vehicles have the same level of automation, subsequent iterations will consider mixed vehicle streams, in order to capture the impacts of varying levels of market penetration.

4.1.1 Scenarios

The use of scenarios enables great flexibility in what is modeled. For example, with the continuing changes in vehicles and the transportation system, as well as the varying levels of automation, even defining a “baseline” is difficult. Some considerations include the following:

a. Will the “baseline” include those forms of automation that exist today?
b. What safety technologies (e.g., alcohol interlocks, V2V safety warnings) will be assumed for future vehicles without automation?
c. What infrastructure changes (e.g., improved traffic signals, integrated corridor management) should be assumed in the absence of automation?
d. What will happen to vehicle size and weight?

Furthermore, there may be uncertainties in how well an automation application performs. The use of scenarios facilitates sensitivity analysis, where the model inputs may be varied to understand and explain the sensitivity of our assumptions.

4.1.2 Submodels

Figure 3, repeated from the executive summary of this report, illustrates the modeling framework, with linkages among components. Forward linkages are shown in black, while the feedback loops are shown in brown. Figure 4 is another view of the framework, with a greater emphasis on data flows and less on feedback.

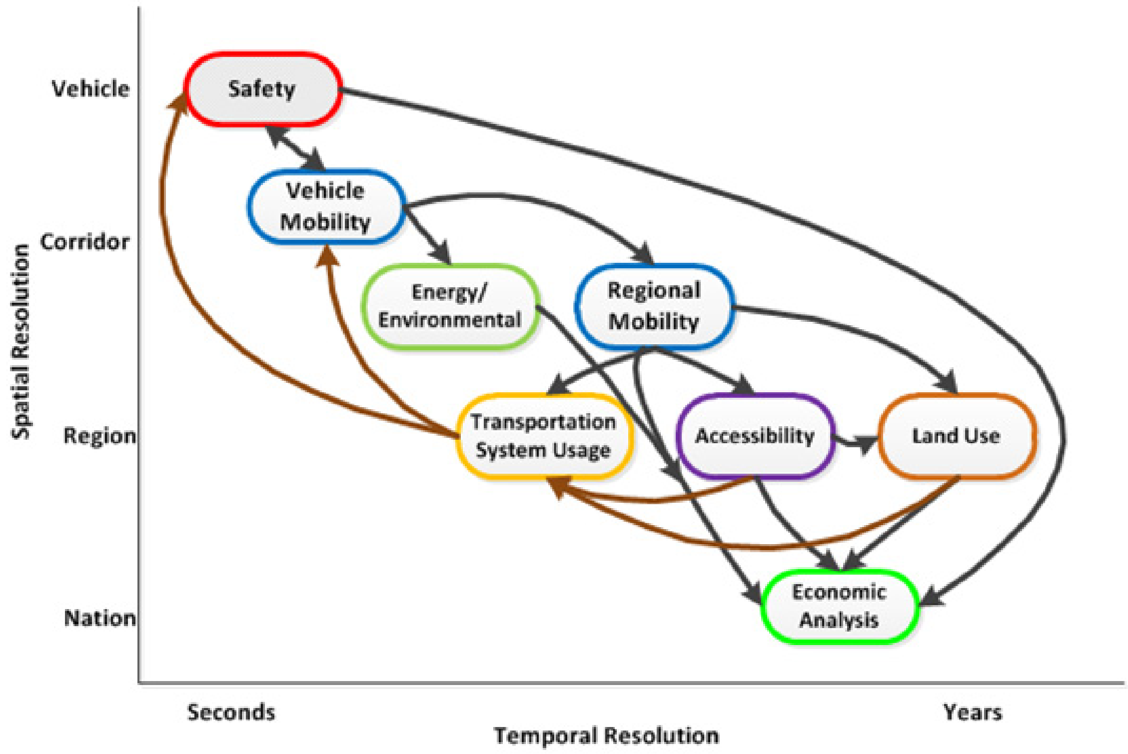

Figure 3. Components of the Modeling Framework (Source: U.S. DOT)

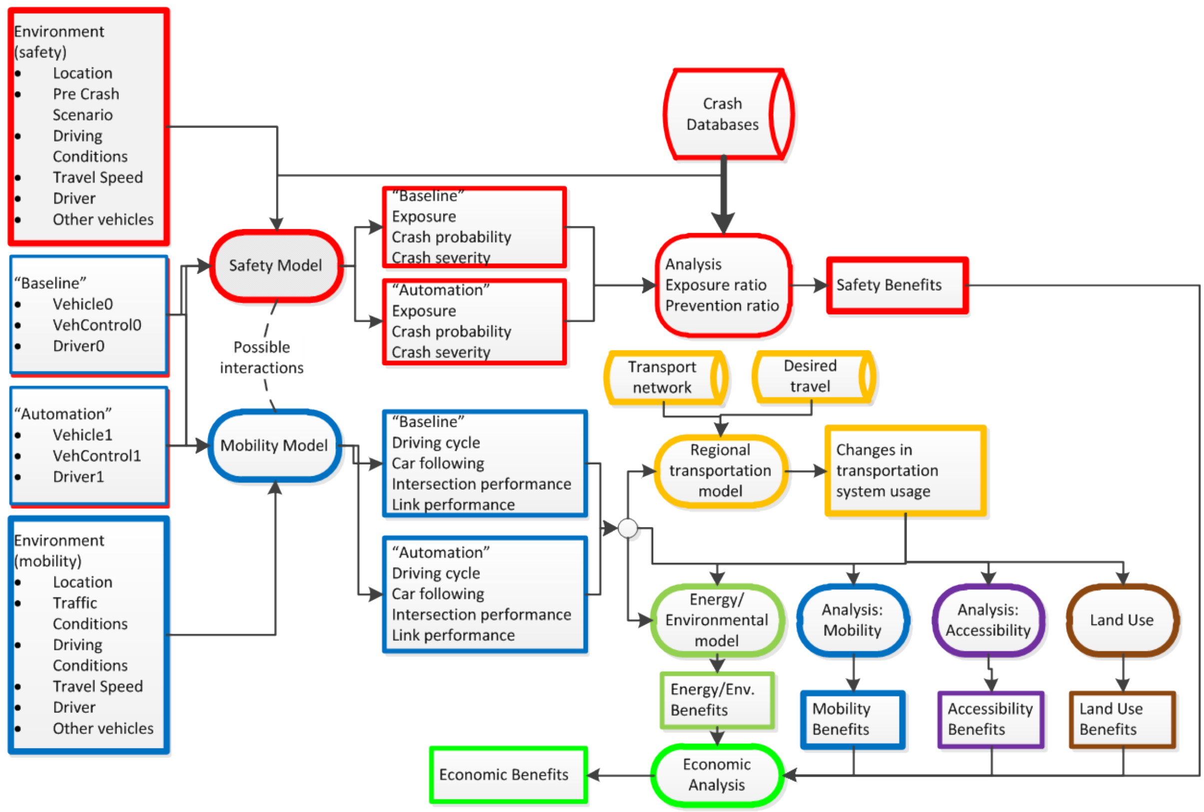

Figure 4. Data Flows in the Modeling Framework (Source: U.S. DOT)

The submodels in Figure 3 and Figure 4 include the following:

Safety (outlined in red). Safety modeling primarily deals with the behavior of driver/vehicle/automation system in the seconds leading up to a potential crash. Thus, safety modeling tends to be performed at an extremely fine-grained level of spatial and temporal resolution, with the results being rolled up into national benefits. Inputs to the safety model include the initial environment, the attributes of the "baseline" and "automation" vehicles, including the vehicle itself (e.g., light vehicle vs. truck), vehicle control (e.g., what level of automation exists), and the driver (e.g., reaction time distribution). Safety modeling then produces a comparison of exposure, crash probability, and crash severity between "baseline" and "automation" vehicles. With these results in hand, further analysis is performed to estimate national safety benefits.

Vehicle and Regional Mobility (outlined in blue). Vehicle mobility deals with car following, gap acceptance, and other detailed aspects of vehicle performance. Regional mobility is at a less fine-grained spatial and temporal resolution, and deals with the performance of a highway corridor, an intersection, or a region. Inputs to the vehicle mobility model include the initial environment, the attributes of the "baseline" and "automation" vehicles, including the vehicle itself (e.g., light vehicle vs. truck), vehicle control (e.g., what level of automation exists), and the driver (e.g., car following behavior). The vehicle mobility model then produces a comparison of driving cycles, car following performance, and intersection performance. Further analysis is done to translate car following and intersection performance into link performance (for example, if headways are reduced by x, then you can move y more vehicles per hour on the link).

There may be interactions between the mobility and safety models. For example, a CACC application may reduce the number of conflicts requiring use of a forward collision avoidance system. Furthermore, both the mobility and safety models take the attributes of the "baseline" and "automation" vehicles as inputs.

The "baseline" and "automation" outputs of the mobility models feed into another set of models, as follows:

- **Energy / Environmental (outlined in green).** A detailed driving cycle (idle time, acceleration, cruise, deceleration) that comes from the mobility modeling being fed into a model that calculates energy consumption and emissions.
- **Transportation System Usage (outlined in yellow).** Travelers will change their travel patterns in response to changes in mobility (for example, if a road becomes less congested, it may receive more use). This part of the framework captures the traveler responses to changes in mobility and accessibility. As such, it drives most of the feedback (depicted as the brown lines).
- **Accessibility (outlined in purple).** Accessibility measures the ability of people to reach desired destinations.
- **Land use (outlined in brown).** Land use addresses the density and mix of development in a particular region.
- **Economic Analysis (outlined in light green).** Many of the other benefits, including reduced cost of crashes and congestion and improved access to jobs, lead to economic benefits.

When viewing Figure 4 as a whole, it is important to remember three things:

1. Feedback may occur at various stages in this process.
2. "Baseline" is in quotes because, for a particular scenario, it may include technologies that are likely to be deployed in the near future, even in the absence of increased automation. It may also include some level of automation, or some set of automation applications.
3. "Automation" is also in quotes because it may mean anything from a single Level 1 automation application to a Level 4 driverless car.

4.1.3 Multiple Timescales

The framework will have several layers, ranging from small time and space scales (micro) to much larger time and space scales (macro). The micro-layer deals with the performance of an application, and uses measures such as following distance and reaction time. The meso-layer deals with the performance of a small part of the transportation system, and uses measures of effectiveness, such as the capacity of a road segment. The macro-layer deals with larger regional and national impacts. See Figure 5.

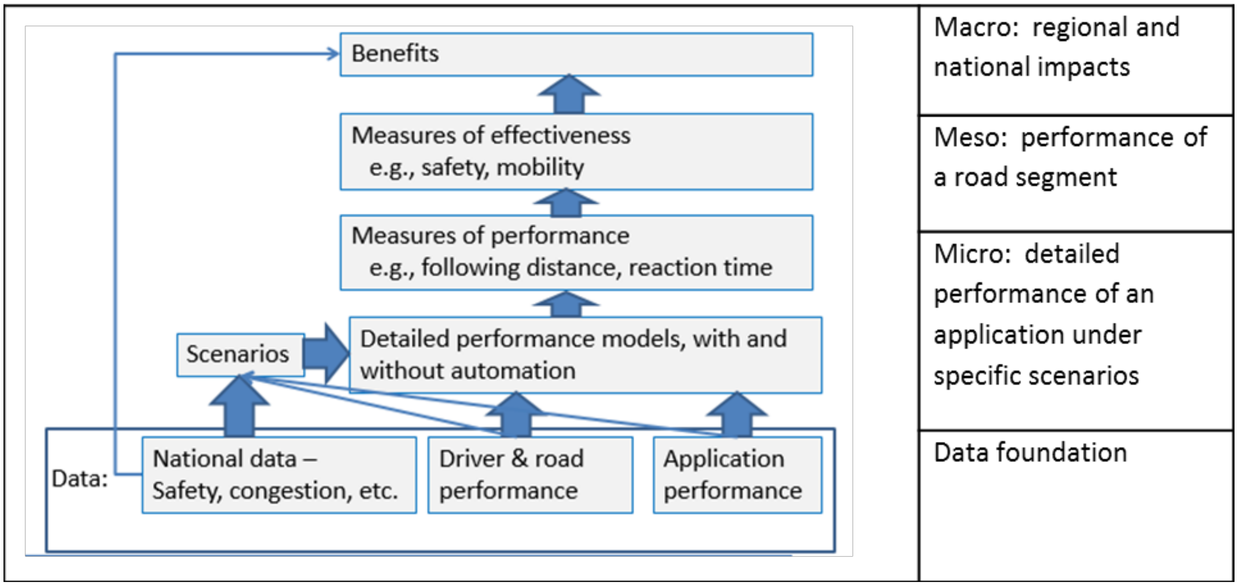

Figure 5. Layers for the Modeling Framework (Source: U.S. DOT)

4.1.4 Incremental Construction

A comprehensive model of the benefits of automated vehicles will be complex. It will involve multiple data sources, multiple scales of time and space, and will make use of multiple existing models and potentially yet-to-be-developed models. An incremental approach to building the framework is proposed, to reduce risk and to show value earlier in the process. The following initial steps are proposed.

4.1.4.1 Step 1: Stream of uniform light vehicles in a single lane

Step 1 will consider the following models and applications:

- Car following for CACC
- Forward collision avoidance

A number of models of vehicles in a single lane have already been created, along with a limited number of test track field tests. Our model can be compared to these existing models and tests to provide an initial validation. Even with this simple model, several benefit areas can be considered:

- Safety. If the lead vehicle is assumed to be stopped or going slower than the host vehicle, the ability to avoid a collision can be assessed.
- Mobility. Automation's impacts on traffic flow instability can be examined.
- Energy / environment. Smoother traffic flow will lead to energy and environmental benefits, the extent to which will be addressed in the model.

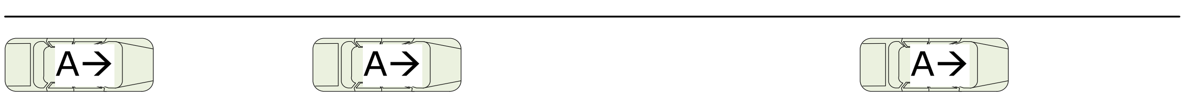

Figure 6. Stream of Uniform Light Vehicles In a Single Lane (Source: U.S. DOT)

4.1.4.2 Step 2: Mixed stream in a single lane

Step 2 will consider various types of vehicles, both with and without automation, sharing the lane. In addition to the applications considered in step 1, it will consider heavy vehicle platooning.

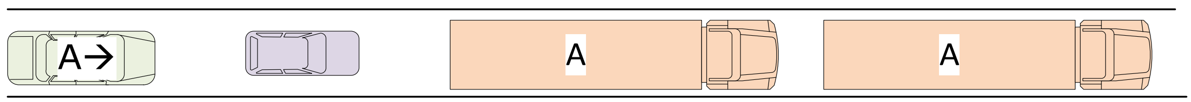

Figure 7. Mixed Stream In a Single Lane (Source: U.S. DOT)

This model, while still very simple, can be used to represent a single managed lane on a freeway with Level 1 automation present.

4.1.4.3 Step 3: Mixed stream in a single lane with traffic control

Step 3 will add a traffic control (such as a traffic signal or stop sign) to the lane. It introduces V2I interactions with their varying forms of wireless communications, and enables preliminary modeling of the intersection management applications. This model can represent a single-lane road with controlled intersections.

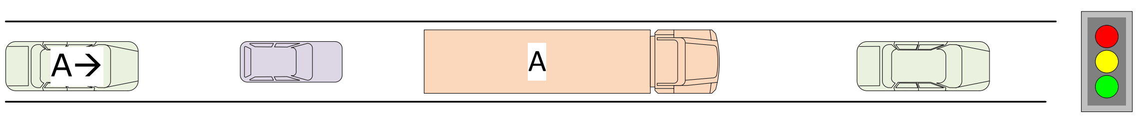

Figure 8. Mixed Stream In Single Lane with Traffic Control (Source: U.S. DOT)

4.1.4.4 Step 4: Mixed stream in several lanes

Step 4 will add multiple lanes, with or without traffic control. It will add the complexity of lane changes, and will enable the modeling of those applications that involve lateral movement of the vehicle.

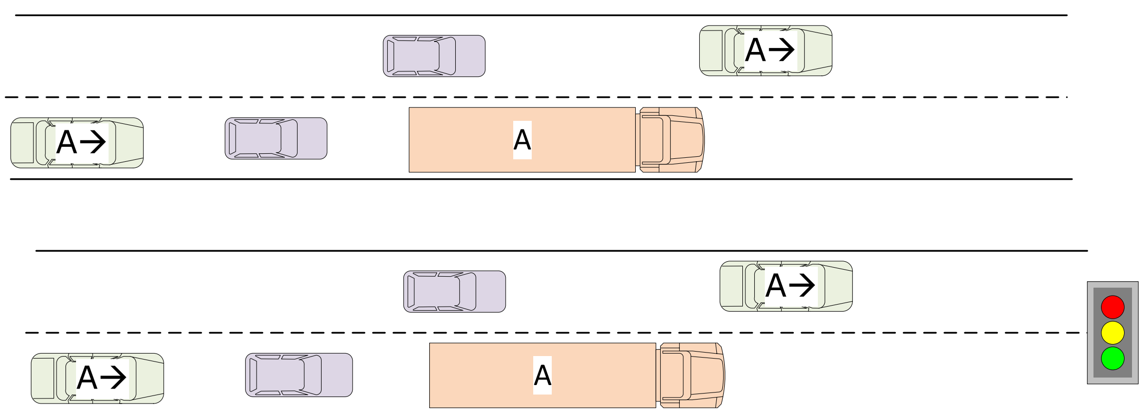

Figure 9. Mixed Stream In Several Lanes (Source: U.S. DOT)

4.1.4.5 Step 5: Corridor

Step 5 will consider a corridor. It will add the complexities of conflicting traffic flows and multiple destinations among vehicles. At this point, it may be possible to model a real street or freeway segment.

Figure 10. Corridor (Source: U.S. DOT)

As an example of a conflict that might arise from multiple destinations, consider the following scenario for eco-approach and departure (Figure 11). Truck A and Car B are both approaching an intersection with a leading protected left turn. Truck A is traveling straight through the intersection and its eco-approach is to slow down well in advance so that it reaches the intersection just after the left-turn portion of the cycle. Meanwhile, car B wishes to turn left, and its eco-approach is to maintain speed, to make the left turn signal. What is the proper course of action, from both an eco-driving and mobility standpoint? These types of questions will be raised throughout the process of developing the framework, and may lead to a number of necessary assumptions for using the framework.

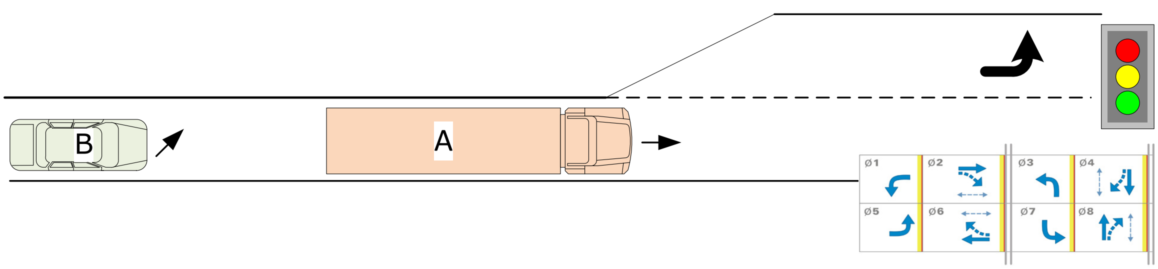

Figure 11. Eco-Approach and Departure with Multiple Destinations (Source: U.S. DOT)

4.1.4.6 Step 6: Region

In order to capture accessibility benefits, network effects, and the interaction between transportation supply and demand, modeling is needed at the regional or subregional level (Figure 12). Here, the car-following and intersection performance results from the detailed models of the previous steps can be converted to a less-detailed traffic microsimulation or into link performance functions. With these new transportation supply functions (the volume/speed/capacity relationship on each link), the interaction between supply and demand can be evaluated.

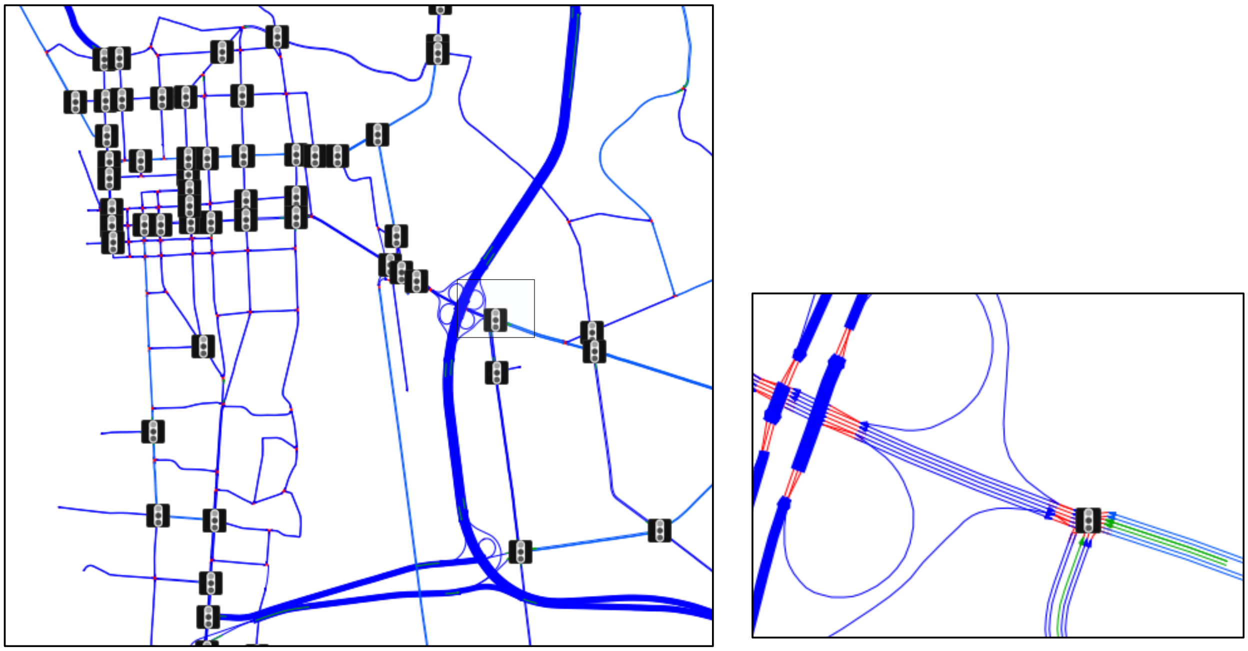

Figure 12. Regional Modeling: Overview and Close-up (Source: U.S. DOT)

4.2 Safety

Safety modeling will be based on the safety impact methodology (SIM) framework (Najm & daSilva, 2000) (Carter, Burgett, Srinivasan, & Ranganathan, 2009). The SIM framework is a systematic approach for evaluating the safety impacts of a new vehicle system. It has been used, for example, to assess the safety impacts of V2V technologies (Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014).

The SIM framework incorporates historical crash, driver performance, and system performance data to enable a rigorous comparison of baseline and treatment vehicle crash conflicts. SIM considers changes in exposure to near-crash situations, crash prevention, and mitigation of crash severity if a crash occurs. It has the flexibility to accommodate many types of automation applications and crashes.

In SIM, the fundamental equation for benefits (Najm & daSilva, 2000) is:

$$\mathbf{B} = \mathbf{N} \times \mathbf{SE}$$

Where:

$\mathrm{B} \equiv$ Benefit obtained from the implementation of automated vehicle functions (e.g., crashes reduced, injuries mitigated)
$\mathrm{N} \equiv$ Annual addressable crash population for automated vehicle functions (e.g., number of crashes, number of injuries)
$\mathrm{SE} \equiv$ System effectiveness of automated vehicle functions

The annual addressable crash population, *N*, can be determined from historical crash databases such as the General Estimates System (GES) and the Fatality Analysis Reporting System (FARS). The system effectiveness, *SE*, is estimated based on the following equation:

$$\mathbf{SE} = \mathbf{1} - \mathbf{ER} \times \mathbf{CPR}$$

Where:

ER ≡ Exposure Ratio, the probability of exposure to a conflict scenario, with and without an automated vehicle function

CPR ≡ Crash Prevention Ratio, the crash probability given that a conflict scenario has been entered, with and without an automated vehicle function

A driving conflict[34] occurs when two vehicles will crash (within some number of seconds) unless a crash avoidance action is taken by either vehicle.

The Exposure Ratio (ER) is defined as the ability of a crash avoidance system to reduce the occurrence of conflicts in normal driving behavior (McMillan, Christiaen, & G.V, 2001) and is estimated with the following:

$$Exposure\ Ratio\ (ER) = \frac{Exposure\ to\ Driving\ Conflicts\ with\ the\ Application}{Exposure\ to\ Driving\ Conflicts\ without\ the\ Application}$$

Typically, the change to drivers' exposure is obtained from field observations during a field operational test (Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014, page 268). Given limited data availability and duration of tests, it is often difficult to quantify changes in exposure. As a result, this parameter is sometimes conservatively assumed to be equal to one. This would assume that a driver's behavior does not change with the introduction of an automated vehicle function.

The Crash Prevention Ratio (CPR) measures crash reduction, given that a conflict has occurred. It is defined as:

$$Crash\ Prevention\ Ratio\ (CPR) = \frac{Crash\ Probability\ with\ the\ Application}{Crash\ Probability\ without\ the\ Application}$$

The CPR can be estimated using the SIM tool, a computer-based simulation of vehicle kinematics and driver/vehicle reaction times, both with and without the application that is being studied (Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014).

[34] A generic timeline of crash phases (Burgett & Srinivasan, 2008) includes the following elements

1. Non-conflict condition
2. A critical event leading to a conflict or an imminent crash. Conflict or imminent crash may be defined in terms of time to collision (TTC). For example, we may define a conflict as occurring when TTC is less than 6 seconds, and the conflict becomes an imminent crash when TTC falls below 2.5 seconds.
3. Conflict
4. Imminent crash
5. Crash
6. Post-crash

The SIM tool is a Monte Carlo-based simulation which uses basic kinematic equations to create a conflict between two vehicles and estimate the probability of a crash, with and without a safety application. The SIM tool requires input on initial conflict conditions, changes in driver performance, and system performance capabilities. The SIM tool outputs the probability of a crash, under the given conditions, with and without a safety application. If a crash occurs, the SIM tool reports impact speeds and Delta V measures for the two vehicles involved.[35] External analysis of the outputs from the SIM tool, in combination with the basic benefits equation yield estimates on potential safety benefits.

Figure 13, from (Carter, Burgett, Srinivasan, & Ranganathan, 2009), illustrates the overall SIM logic.

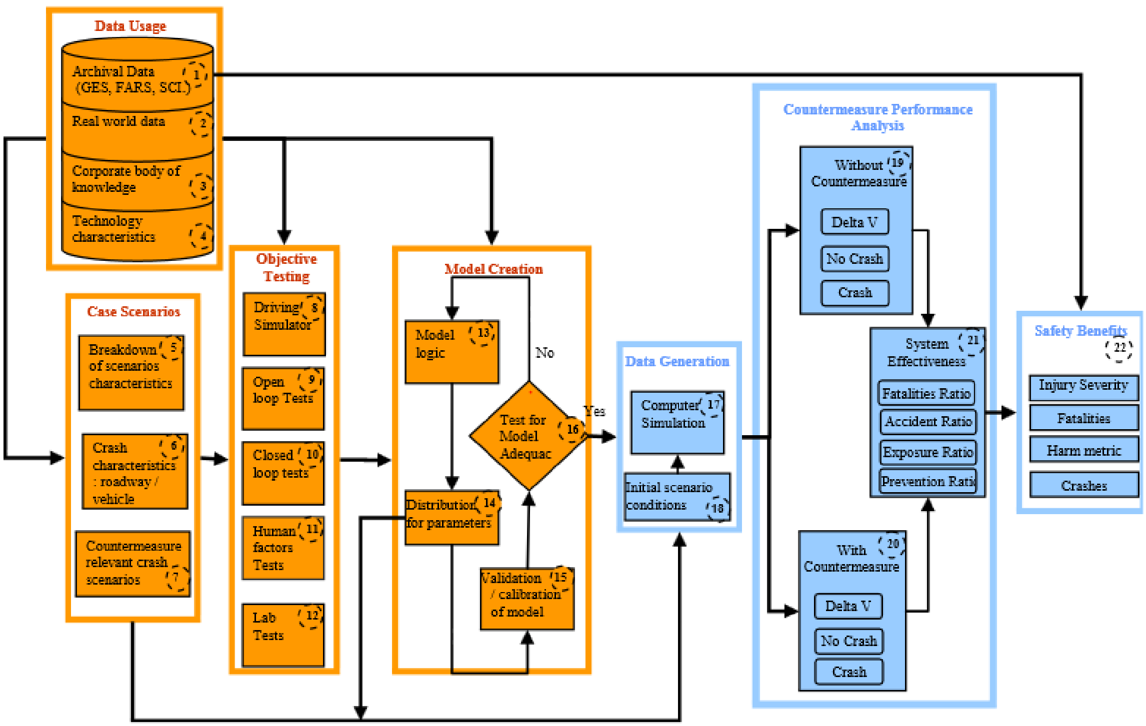

Figure 13. Safety Impact Methodology Overall Logic (Source: Carter, Burgett, Srinivasan, & Ranganathan, 2009)

Figure 14, from (Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014), illustrates the logic of the SIM software tool. The data sources used as input into the SIM tool validate the conflict and accuracy of the CPR. SIM includes both the detailed modeling of the vehicle-to-vehicle interaction, and the roll-up to national impacts.

[35] Delta V is the instantaneous change in speed a vehicle experiences at the time of crash. Delta V can be correlated to injury level experienced by occupants within a vehicle.

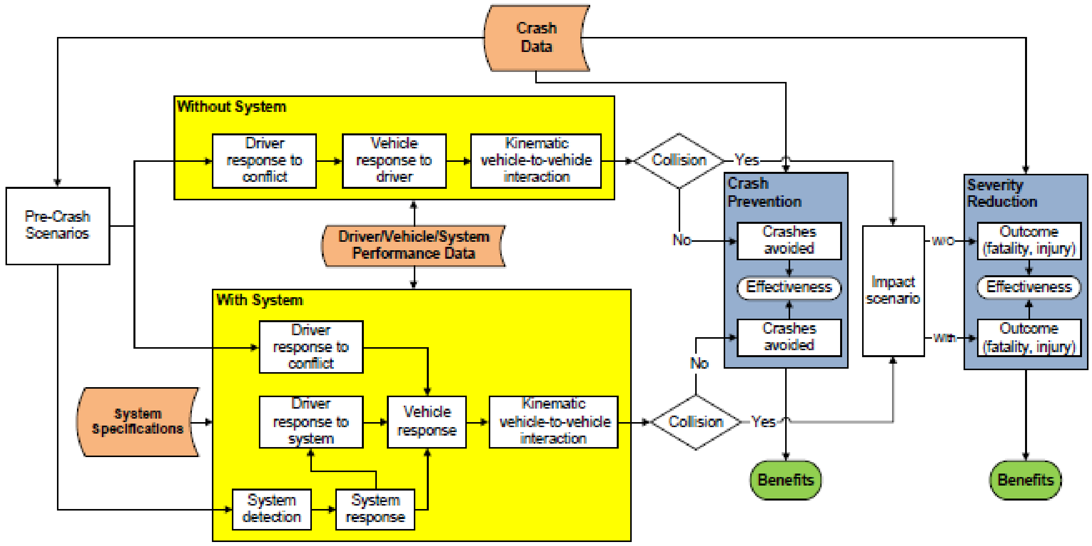

Figure 14. Safety Impact Methodology Software Tool Logic (Source: Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014),

4.2.1 Relationship to Other Parts of the Framework

Safety has clear relationships with vehicle mobility, transportation system usage, and economic benefits (Figure 15).

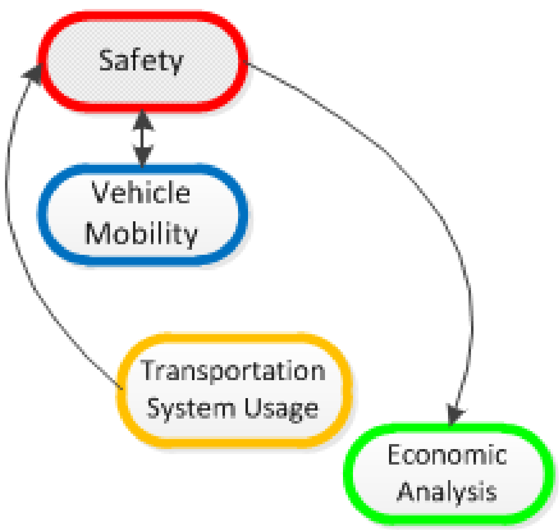

Figure 15. Relationship between the Safety Submodel and the Rest of the Framework (Source: U.S. DOT)

Some automation applications involve a mobility / safety tradeoff. For example, the car following function of a CACC application might be set for a long following distance, which may improve its safety impacts, but would have a detrimental effect on lane throughput, and thus vehicle mobility. On the other hand, since crashes are a significant cause of congestion, fewer crashes would improve vehicle mobility.

Changes in transportation system usage will also affect safety. If the crash rate per 100 million vehicle miles remains constant, but vehicle-miles increases, then the number of crashes will increase. Additionally, improved safety has a clear economic benefit, in terms of reduced crash related costs, and reduced time lost from work.

Further research is required to fully understand the direct relationship between the safety impact of automated vehicle applications and their effect on other parts of the framework.

4.2.2 Detailed Modeling

Detailed modeling starts with a thorough understanding of the automated vehicle application being modeled as well as its expected effects on the host and other nearby vehicles. A thorough understanding of an automated vehicle application includes detailed operational conditions of the application and its intended use. Table 3 shows the operational conditions and road types for some automation applications.

Table 3. Summary of L1–L4 Automated Vehicle Functions

Automation Level	Automated Vehicle Function	Operational Conditions	Roadways
L0	Alcohol Detection Technology	Drunk Driver	All Roads
	Back-Up System	Low Speeds	All Roads
	Drowsy Detection System	Drowsy Driver	All Roads
	Warning Systems (BSW/LCW, FCW, IMA, LTA, RDCW)	Speeds > 25 mph	All Roads
L1	ACC and Cooperative ACC	High Speeds	Highway
	Automated Emergency Braking	Imminent Crash	All Roads
	Automated Parking	Low Speeds	Urban
	Automated Roadwork Assistance	Low Speeds	Work Zone
	Electronic Stability Control	Loss of Control	All Roads
	Ignition Interlock	Drunk Driver	All Roads
	Pedestrian Crash Avoidance and Mitigation	Speeds < 45 mph	All Roads
L2	ACC w/Lane Centering	Speeds ≤ 100 mph	Highway
	ACC w/Lane Keeping and Lane Change	Speeds < 75 mph	Highway
	ACC w/Lane Keeping, Lane Change, and Merge	Speeds ≤ 81 mph	Highway
	Traffic Jam Assist	Speeds ≤ 37 mph	Urban
	Automated Roadwork Assistance	Low Speeds	Work Zone
	Automated Parking	Low Speeds	Urban
L3	Automated Highway Driving	High Speeds	Highway

Automation Level	Automated Vehicle Function	Operational Conditions	Roadways
	Cooperative Convoy (Close-Headway Platooning)	Speeds ≤ 56 mph	Highway
	Emergency Stopping Assistance	Incapacitated Driver	Highway
	Automated Parking	Low Speeds	Urban
L4	Automated Urban Shuttle	Low Speeds	Urban
	Automated Universal Shuttle	All Speeds	All Roads
	Emergency Stopping Assistance	Incapacitated Driver	All Roads
	Automated Parking	Low Speeds	Urban

Automated vehicle applications may only operate under specific conditions. These conditions can be constrained by vehicle location, speed, and/or dynamics. Based on these constraints, automated vehicle applications may only address specific pre-crash scenarios. Pre-crash scenarios depict specific vehicle movements and dynamics as well as the critical event occurring immediately prior to the crash. Table 4, from (Najm, Smith, & Yanagisawa, 2007), lists the pre-crash scenarios. An automation application may address one or more of these pre-crash scenarios.

Table 4. Pre-Crash Scenarios

Pre-Crash Scenario	Crash Type
Vehicle Failure	Run-Off-Road
Control Loss with Prior Vehicle Action	
Control Loss without Prior Vehicle Action	
Running Red Light	Crossing Paths
Running Stop Sign	
Road Edge Departure with Prior Vehicle Maneuver	Run-Off-Road
Road Edge Departure without Prior Vehicle Maneuver	
Road Edge Departure While Backing Up	
Animal Crash with Prior Vehicle Maneuver	Animal
Animal Crash without Prior Vehicle Maneuver	
Pedestrian Crash with Prior Vehicle Maneuver	Pedestrian
Pedestrian Crash without Prior Vehicle Maneuver	
Pedalcyclist Crash with Prior Vehicle Maneuver	Pedalcyclist
Pedalcyclist Crash without Prior Vehicle Maneuver	
Backing Up into Another Vehicle	Backing
Vehicle(s) Turning – Same Direction	Lane Change
Vehicle(s) Parking – Same Direction	
Vehicle(s) Changing Lanes – Same Direction	
Vehicle(s) Drifting – Same Direction	
Vehicle(s) Making a Maneuver – Opposite Direction	Opposite Direction
Vehicle(s) Not Making a Maneuver – Opposite Direction	
Following Vehicle Making a Maneuver	Rear-End
Lead Vehicle Accelerating	
Lead Vehicle Moving at Lower Constant Speed	

Pre-Crash Scenario	Crash Type
Lead Vehicle Decelerating	
Lead Vehicle Stopped	
LTAP/OD at Signalized Intersections	Crossing Paths
Vehicle Turning Right at Signalized Intersections	
LTAP/OD at Non-Signalized Intersections	
Straight Crossing Paths at Non-Signalized Intersections	
Vehicle(s) Turning at Non-Signalized Intersections	
Evasive Action with Prior Vehicle Maneuver	Run-Off-Road
Evasive Action without Prior Vehicle Maneuver	
Non-Collision Incident	Other
Object Crash with Prior Vehicle Maneuver	Object
Object Crash without Prior Vehicle Maneuver	
Other	Other

4.2.1.1 Inputs and Outputs

Several sources of real-world data provide the input for the SIM. Data from these sources feed into the basic safety benefits equation and the SIM tool to estimate safety benefits. Field operational tests, driving simulator experiments, human factors-based test track studies, and historical crash data produce driver-vehicle performance data with and without assistance of the safety applications. Elements of driver performance include the type of reaction (steer or brake), the reaction time, and the reaction level (e.g., how hard are the brakes applied). Field operation tests and system characterization test track experiments provide system performance and capability data. Elements of system performance include activation (when, in terms of time-to-collision or distance, is the system activated), and system action (warn, brake, steer, etc.). Crash databases contain historical crash statistics which provide baseline values for initial conditions of pre-crash scenarios and driver performance.

Outputs include the reduction in conflicts (situations where evasive action is required to avoid a collision), reduction in collision, and reduction in impact speeds (Delta V).

4.2.1.2 Data

For accurate assessment of the potential safety benefits of automated applications, statistically relevant data are needed in several areas:

- Performance of the human driver, with and without the automation application
- Performance of the vehicle/automation system, with and without driver intervention, and
- Historical crashes

Elements of human driver performance include data that allows the driver and vehicle to successfully avoid conflicts, or should conflicts occur, avoid crashes. Avoidance of conflicts and crashes includes perception of the environment (e.g., other vehicles) as well as timely and appropriate reaction to changes in the environment.

More specifically, data elements and possible sources in each of the three areas above are presented below in Table 5.

Table 5. Safety Data and Sources

Needed Data	Source(s)
Performance of the human driver - **Initial driving behavior** - **Perception of hazards (distraction)** - **Reaction time** - **Appropriate response** - **Magnitude of response**	Naturalistic driving data - Exposure to conflict situations - Driver performance Human factors simulation/test track studies - Driver performance Crash data
Performance of the AV system - **Initial driving behavior** - **Perception of hazards** - **System delay** - **Appropriate response** - **System reliability**	Tests of AV systems - AV system capability - AV system performance
Data on crashes - **Numbers of crashes** - **Pre-crash scenarios** - **Road and driver information** - **Crash severity (injury, fatality)**	Data sources (GES, FARS) are well established, but have gaps. Distracted driving behavior and speed are not reliably reported

Figure 16 illustrates the data flows for the SIM.

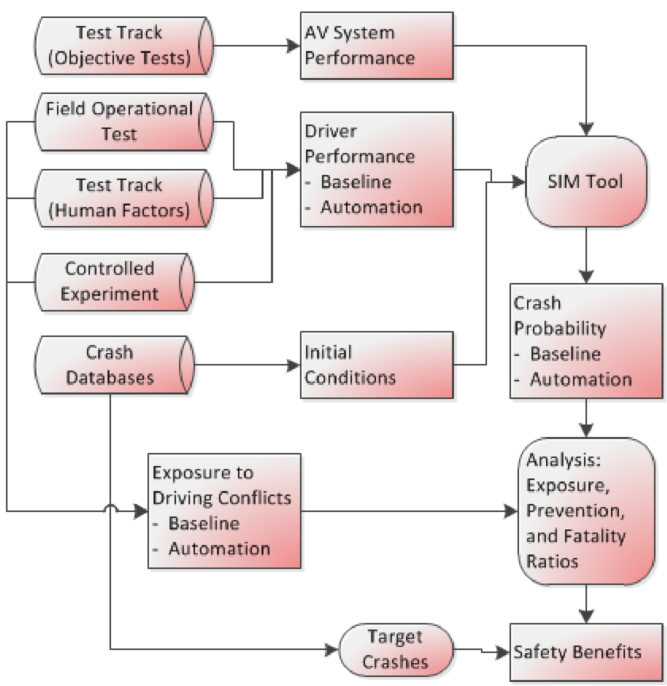

Figure 16. SIM Data Flows (Source: U.S. DOT)

4.2.1.3 Challenges in safety modeling

Fundamental assumptions of SIM modeling include the following:

1. It is designed to address specific types of crashes that were pre-selected based on data needs (for example, rear-end crashes are historically frequent and can be addressed through a Forward Collision Avoidance system). If an unintended consequence of an automation system is a new type of crash, the new crash will not be captured, unless the supporting data and SIM[36] are adjusted to address it.
2. It does not deal with second order impacts (for example, arising from changes in VMT). Fortunately, other parts of the framework will address these second order impacts.
3. It only deals with crashes. The SIM tool is not currently designed to address non-crash mishaps (for example, a passenger falling as he alights from a bus).

Safety modeling has traditionally dealt with only a host and target vehicle. With automation, the interactions of multiple vehicles (for example, in a platoon) become more significant, and will need to be addressed.

The data also present several challenges.
Safety analysis must consider deployment and penetration rates of the automated vehicle functions, availability and reliability of these functions, and driver use and acceptance when estimating potential benefits.

In the area of human driver performance, a gap is the performance of the human driver in the presence of automation. Will the driver lose situational awareness, and thus be unable to respond appropriately to a situation that the automated system can't handle? A related question is the amount of notice required to successfully transition from automated to manual operation.

Another challenge is that of redefining the baseline crash statistics as higher levels of automated safety applications are introduced into the vehicle fleet over time. The simultaneous deployment of several connected vehicle and automation applications may create an overlapping safety benefit.

For example, an automated emergency braking system which is part of the baseline may lead to a reduction in rear-end crashes, while doing nothing for exposure to near-crash situations. Meanwhile, an ACC system may help to reduce the ***exposure*** to near-crash situations. Careful accounting will be necessary to accurately assess the contributions of the two systems to safety.

Future crash data will need to be analyzed to identify any major shifts or trends in the crash data with the deployment of higher levels of automation as compared to the baseline crash data of today.

In the area of automated system performance one gap is that of simply defining the characteristics of an automation system. Although high level descriptions exist, manufacturers may develop subtly different systems, and a complete picture of system performance may not be readily available. One key question is the degree to which automated vehicles will recognize each other as such, and the degree to which they make use of information on the other vehicle's capabilities.

Knowledge of the automation system's ability to avoid driving conflict situations may not be well defined. In their recent paper, (Sivak & Schoettle, 2015) point to the safety benefit of the predictive knowledge of an experienced driver, asking if automation could match that predictive knowledge. For example, an experienced human driver may move one lane to the left on a freeway because she knows that a downstream on-ramp is likely to have substantial conflicting traffic. With map and traffic data, an automation system could easily handle

[36] SIM includes the SIM tool. Adjusting pre-crash scenarios would require adjustment of the kinematics within the SIM tool.

this example, but there may be other examples of predictive behavior that are neither easily handled by automation nor easily modeled.

Finally, the behavior of the automation system in unusual situations may not be well known, although in some cases the response may lead to a crash. For example, the system may fail to respond to a hazard. Conversely, it may respond inappropriately to a non-hazard (e.g., braking hard for a piece of paper in the road).

The data sources for crashes also have well-known limitations. For example, distracted driving behavior and speed are not reliably reported. Data can be provided from more in-depth crash databases; however, these databases contain a limited number of cases and therefore are not nationally representative.

4.2.3 Assessing National Impacts

To assess national safety impacts, SIM uses national crash data, and the relationships between crash type, injury severity, and Delta V.

Consider the following example that uses made-up data:

1. We have a forward crash avoidance / cruise control system that is designed to prevent crashes in a freeway environment with a stopped lead vehicle
2. National crash data tells us there are 100,000 annual rear-end crashes with lead vehicle stopped in a freeway environment.
3. Field tests and naturalistic driving data tell us that without the system, for X miles of driving, there are 60 conflicts, leading to 15 crashes
4. Field tests tell us that with the system, the conflicts dropped from 60 to 45. Therefore, the exposure ratio is 0.75 = 45 / 60
5. SIM tool modeling tells us that:
    a. Without the system, the probability of a crash occurring in a conflict is 25 percent
    b. With the system, the probability of a crash occurring in a conflict is reduced to 20 percent
    c. Therefore, the prevention ratio is 0.8 = 0.2 / 0.25

Recalling the fundamental equation for benefit:

*B = N x (1 – ER*CPR),* we calculate that 40,000 crashes are avoided (Table 6).

40,000 = 100,000 x (1 – 0.75*0.8)

Table 6. Calculation of Crashes Avoided

	Conflicts	Probability of crash given a conflict	Exposure ratio (ER)	Prevention ratio (PR)	Crashes avoided
Without	60	0.25			
With	45	0.2	0.75	0.8	40,000

Further, if a crash is not avoided, it is possible for an automated vehicle function to reduce the severity of the crash by reducing the potential impact speed. Given a reduced impact speed, it is feasible to estimate the potential reduction in injuries by correlating the resulting impact speed into Delta V, than correlating Delta V into known injury risk curves. Figure 17 illustrates an example of a set of harm curves for intersection crashes, based on equations from (Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014), which translate Delta V into injury. A reduction in Delta V would result in a lower probability of injury. MAIS refers to the Maximum Abbreviated Injury Scale, ranging from MAIS 1 (minor injury) to MAIS 5 (severe injury). MAIS 6 is a fatality.

Potential benefits for automated applications are a combination of crashes avoided; then given a crash has occurred, the reduction in impact speed, reducing the potential for injury and providing injury mitigation benefits.

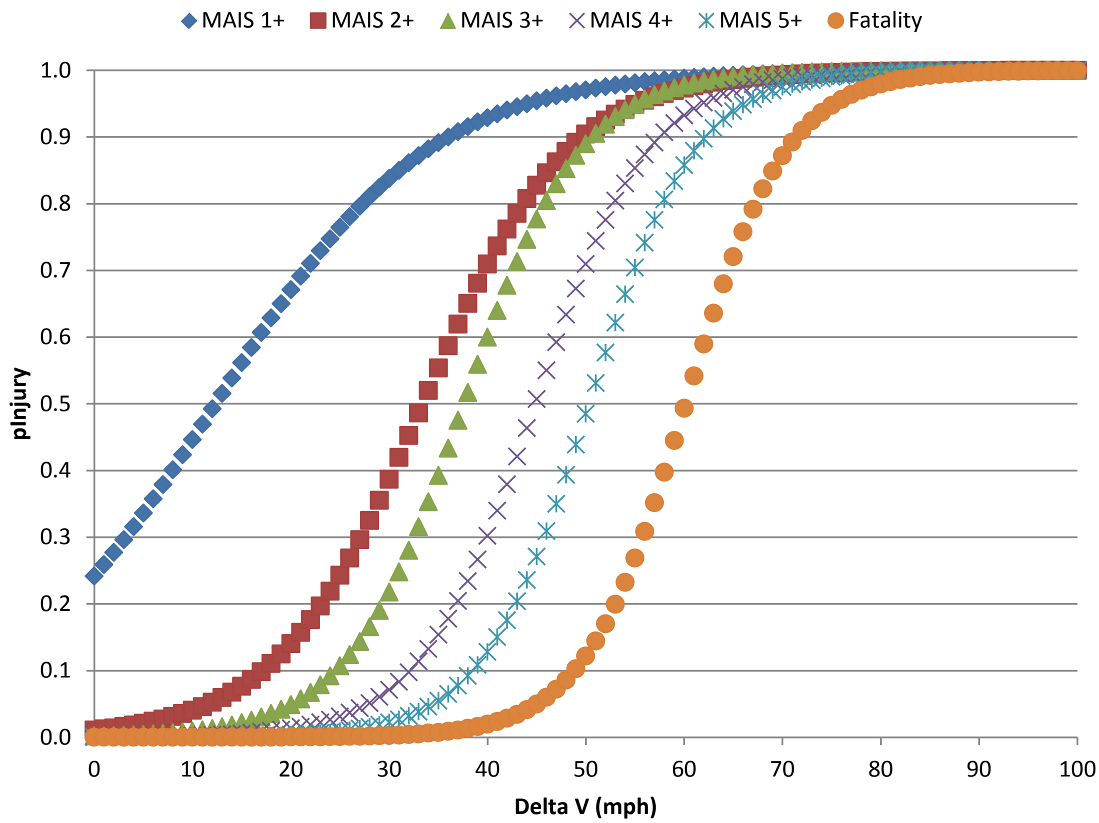

Figure 17. Harm Curves Depicting the Probability of Injury Given Delta V (mph) (Derived from Harding, Doyle, Sade, Lukuc, Simons, & Wang, 2014)

4.3 Vehicle and Regional Mobility

4.3.1 Description of the Approach

As indicated in section 4.1, we will incrementally construct a microsimulation model that will evaluate each of the applications first in a simple single lane then progress to more complex road networks. During this phase we will also be varying the composition of the fleet both in terms of vehicle type and market penetration of the automation application. In addition, we will also study each application in an incremental fashion, starting with idealized models and then building to more realistic road conditions. This approach will allow us to build upon lessons learned as we progress and also provide us with the information required to accurately model the composition of the full fleet of vehicles in the future. For instance, when we look to evaluate vehicles with full automation at low market penetration rates, we should not assume that the other vehicles in the model have no automation. Rather, we should assume that when full automation is available, there will be a sizable number of vehicles on the road with lower forms of automation, including Traffic Jam Assist and CACC.

Another benefit of our approach is that it will give us the ability to understand the incremental mobility benefits of each application. As illustrated in Figure 18, when each application is introduced into the fleet, it will affect the “mobility baseline,” and therefore the impact of the application will be measured relative to the market penetration and performance of the previously introduced applications.

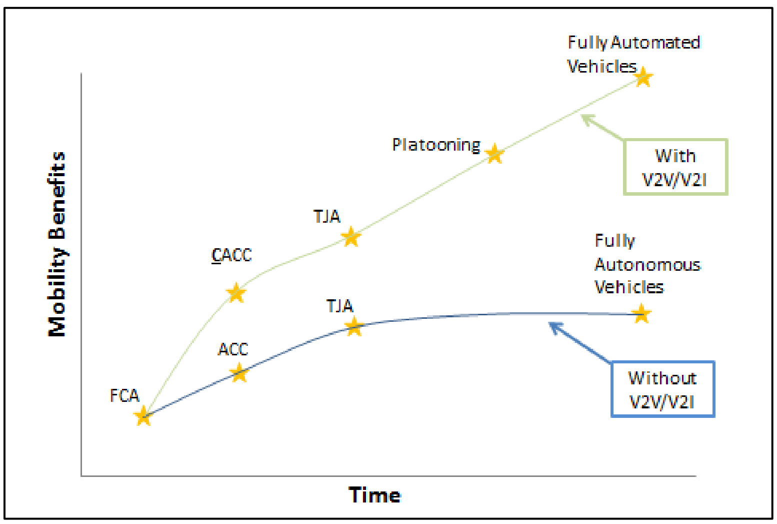

Figure 18. Notional Timeline for Application Adoption and Associated Mobility Benefits (Source: U.S. DOT)

Figure 18 also indicates how we plan to evaluate the impact of V2V and V2I on the mobility benefits of automation. While the benefit information in Figure 18 is notional, there have been a number of studies which have indicated there is a significant difference in mobility performance between CACC (requires V2V) and ACC (no V2V). Our approach will also give us the opportunity to compare the mobility benefits of fully automated vehicles vs. fully autonomous vehicles, which is important information for developing a cost-benefit analysis for V2V/V2I.

While we have discussed our framework for evaluating the mobility benefits, we have not yet determined the specific tools and methods for conducting the analysis primarily because we anticipate working with a third party who will perform the modeling. The Volpe team will use the Small Business Innovation Research (SBIR) vehicle to identify a partner who will conduct some of our analysis. This is not to say that Volpe will not do any of the modeling in-house, but we want to ensure that there is alignment with our partners regarding methods and tools before we define our process.

4.3.2 Relationship to Other Parts of the Framework

A relationship exists between mobility and every other component of the framework. Vehicle mobility has a direct relationship with the safety, energy/environmental, and transportation system usage submodels. Regional mobility has a direct relationship with the transportation system usage, accessibility, land use, and economic analysis submodels. Vehicle and regional mobility submodels also have a direct relationship with each other. These relationships are shown in Figure 19.

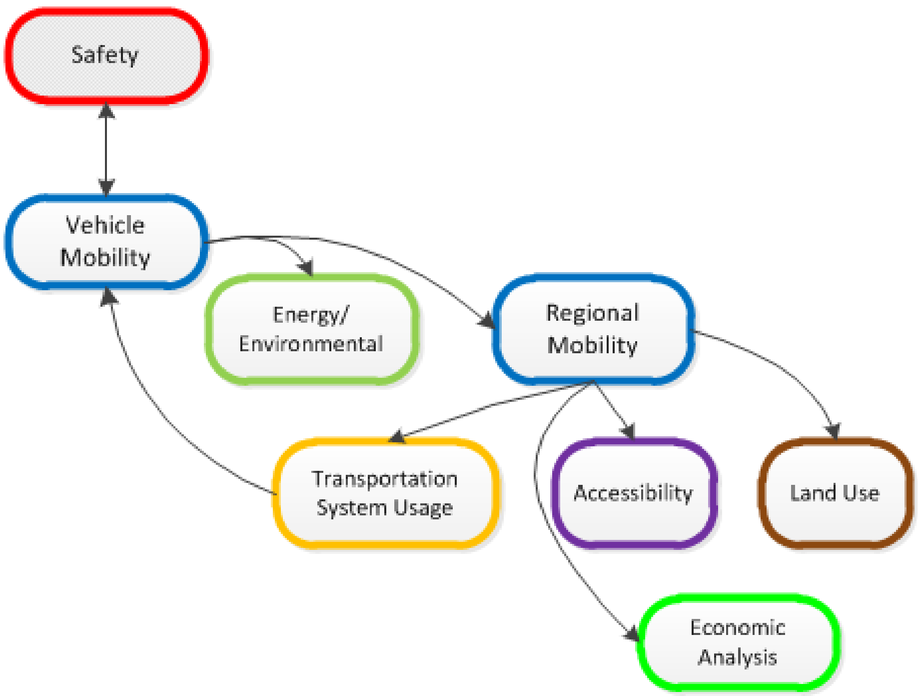

Figure 19. Relationship Between the Vehicle and Regional Mobility and the Rest of the Framework (Source: U.S. DOT)

Changes in transportation system usage will have the largest impact on vehicle mobility. However, given that traffic accidents are a significant cause of traffic congestion, there is also a link between mobility and safety. This will be particularly important for evaluating the mobility benefits of Forward Crash Avoidance (FCA), which is primarily cited for its safety benefits. However, if FCA is able to reduce the number of traffic incidents, then we anticipate that we should observe mobility benefits, particularly when evaluating the regional mobility impact.

4.3.3 Inputs and Outputs

A multitude of data are required to conduct both micro and macroscopic traffic simulation modeling. Rather than list the basic information required to construct a model (e.g., origin-destination pairs, vehicle size, network geometry, etc.) Table 7 provides a list and description of additional inputs that are unique to this study.

Table 7. Inputs for Mobility Modeling

Input	Description
Application design	Information relating to how and when each of the applications be programmed to perform (e.g., detection distance, braking/acceleration parameters, applicable speeds and level of service).
Application performance	Understanding how factors such as weather or road design may impact the ability to engage the application or affect its reliability
Market penetration	What percentage of vehicles in the fleet mix will have the application available over time and how this might vary between vehicle types (e.g., freight trucks become early adopters). This also requires knowing/assuming which year the application will be commercially available.
Application use	This includes an understanding of what percent of drivers will use the application if the vehicle is equipped and if various settings are available which ones drivers might select.
Mobility baseline	As previously discussed in section 4.3.1, we anticipate the mobility baseline will change with the successive introduction of vehicle applications.
Human driver behavior	It is reasonable to assume that human driver behavior will change as a result an application. This includes of both the drivers in the vehicle equipped with the application (FCA leads drivers to be more aggressive) and how drivers in non-equipped vehicles interact with equipped vehicles. A driver may be more willing to accept a smaller merge gap if they believe the following vehicle will stop because it is automated-thereby causing the automated vehicle to hard brake.
Other road user behavior	Behavior of other road users, such as drivers of non-automated vehicles, pedestrians and bicyclists, may negatively affect the mobility performance of automated vehicle systems.

In the early stages, outputs of the models will vary based on the road network and application being studied. For example, CACC on a single-lane highway will be discussed in terms of Veh/lane/hr but the mobility impact of forward collision avoidance will be studied at a regional level and therefore discussed using a metric such as average trip time. However, given that our study will eventually result in the generation of regional and national models that evaluate the impact of each of these applications operating simultaneously, we anticipate that the benefits of each application will be compared using the same regional mobility metric (average trip time, travel time index, etc.). This is an exciting prospect since the mobility performance data for each application in today's literature cannot be directly compared due to the inability to convert between metrics such as veh/ln/hr and average trip time.

Finally, it is our intention to describe the benefits of each application at the national level. Since it is not feasible to construct a model that simulates traffic flow across the entire nation, we will need to extrapolate findings at the regional level to the national level. Our intention is to use existing regional models from more than one metropolitan region and to evaluate the benefits of each application within each region. By doing so, we can understand how the benefits vary across regions and can use that information to extrapolate benefits to the national level. We plan to identify which regional models we will use early on in the implementation phase, or if we should instead develop a generic regional grid given that a calibrated traffic set will not be required for this study. This will allow us to identify which road designs (intersection types, number of highway lanes, etc.) need to be evaluated at the microsimulation level so we can accurately code the regional/macro simulation model. Additional inputs we will use to evaluate the national benefits are annual reports on the cost of congestion.

4.3.4 Data Sources

For much of the information listed in Table 7, we will use information available in the literature, including surveys or technical specification available from vehicle manufacturers. If we are unable to find a valid reference source for our model assumptions, we will seek out the input of professionals within the community. Information regarding the national cost of congestion will be drawn from annual reports such as the Annual Urban Mobility Report published by the Texas A&M Transportation Institute. To leverage the use of existing regional transportation models, we will request to receive any planning models that may be available through a traffic management association (TMA).

4.3.5 Challenges

Two challenges include the investment and complexity of scaling from traffic simulation at a street level to the regional level, and the sensitivity of existing simulation packages to the changes in driver/vehicle behavior that automation might bring.

The development of traffic simulation models is complex and time consuming. A recent California PATH report that analyzed the development of simulation models for 31 California highway corridors found that the average time it took to generate and calibrate the model was 34.4 months at an average cost of ~$948,000. (Dion, Sivakumaran, & Ban, 2012). The majority of modeling effort is the calibration of the model, which we may also be able to avoid if we perform initial testing with our own regional traffic grid. To further ensure that we can develop a cost-effective and time-appropriate simulation model, we will seek to limit the required accuracy of the model relative to the sensitivity of our assumptions. That is to say, we will not need a model that is calibrated to be accurate within 1 minute of observed travel times, when the variability alone of how CACC will perform will have a ±5 minute impact.

The sensitivity of simulation models to the changes in driver/vehicle behavior that automation might bring is also of concern. Although simulation packages employ their own car following submodels, many of which are based upon completely different methodologies, once the models are calibrated each program can deliver similar results. The question is whether the program will continue to deliver accurate results with new parameters (such as a faster reaction time with CACC). Furthermore, the lane change/merging sub models may not be fully representative of human drivers and may need to be fundamentally altered to simulate cooperative lane changes in a V2V environment. The lane-change submodel will have a significant impact when studying the performance of applications that conduct lane changes, namely platooning and automated/autonomous vehicles.

4.4 Energy / Environment

4.4.1 Description of the Approach

A number of studies have linked microsimulation modeling to microscopic fuel consumption and emissions models in order to estimate environmental impacts analysis (Alam, Ghafghazi, & Hatzopoulou, Traffic Emissions and Air Quality Near Roads in Dense Urban Neighborhood: Using Microscopic Simulation for Evaluating Effects of Vehicle Fleet, Travel Demand, and Road Network Changes, 2014), (Chamberlin, Holmen, Talbot, & Sentoff, 2013), (Abou-Senna & Radwan, Developing a Microscopic Transportation Emissions Model to Estimate Carbon Dioxide Emissions on Limited-Access Highways, 2014), (Abou-Senna & Radwan, Microscopic Assessment of Vehicular Emissions for General Use Lane and Managed Lanes: A Case Study in Orlando, Florida, 2014), (Talbot, Chamberlin, Holmen, & Sentoff, 2014) (Veeregowda, Lin, & Herman, 2015) (Lin, Chiu, Vallamsunder, & Song, 2011), (Song, Yu, & Zhang, 2012) and (Chamberlin, Choices to Make When Conducting a Hot-Spot Analysis Using MOVES, 2012). We will be using a similar methodology, utilizing a second-by-second drive schedule output characterizing driving behavior from the mobility analysis as a key input into MOVES2014 to obtain fuel consumption and emissions. MOVES2014 was chosen because of its availability as a regulatory tool as well as its robust methodology.

MOVES2014 at the project level, used principally for this analysis, is capable of calculating emission rates by roadway link based on a variety of inputs, including vehicle type, age, fuel, speed, acceleration, idling times, number of cold starts, soak times as well as meteorological data and road-link characteristics. The key parameters among these inputs are those that affect operating mode distribution for each link, such as velocity acceleration, idling, and hot- and cold-starts. Where applicable, non-key parameters utilize default national-scale data embedded in MOVES, which are discussed in greater detail in the Inputs section.

For light-duty vehicles, running emissions rates are estimated through assignment into operation mode 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 can be calculated using the following equation (Assessment and Standards Division, Office of Transportation and Air Quality, US EPA, 2011)

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

In which,
A = tire rolling resistance term (kW sec/m)
B = rotational resistance term (kW sec^2/m^2)
C = aerodynamic drag term (kW sec^3/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 8. Definition of MOVES Operating Modes for Running-Exhaust Operation

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			$a_t \le -2.0$ OR ($a_t < -1.0$ AND $a_{t-1} < -1.0$ AND $a_{t-2} < -1.0$)
1	Idle		$-1.0 \le v_t < 1.0$	
11	Coast	$VSP_t < 0$	$1 \le v_t < 25$	
12	Cruise/Acceleration	$0 \le VSP_t < 3$	$1 \le v_t < 25$	
13	Cruise/Acceleration	$3 \le VSP_t < 6$	$1 \le v_t < 25$	
14	Cruise/Acceleration	$6 \le VSP_t < 9$	$1 \le v_t < 25$	
15	Cruise/Acceleration	$9 \le VSP_t < 12$	$1 \le v_t < 25$	
16	Cruise/Acceleration	$12 \le VSP_t$	$1 \le v_t < 25$	
21	Coast	$VSP_t < 0$	$25 \le v_t < 50$	
22	Cruise/Acceleration	$0 \le VSP_t < 3$	$25 \le v_t < 50$	
23	Cruise/Acceleration	$3 \le VSP_t < 6$	$25 \le v_t < 50$	

Operating Mode	Operation Mode Description	Vehicle-Specific Power (VSP_t, kW/metric ton)	Vehicle Speed (v_t, mph)	Vehicle Acceleration (a_t, mph/sec)
24	Cruise/Acceleration	$6 \le VSP_t < 9$	$25 \le v_t < 50$	
25	Cruise/Acceleration	$9 \le VSP_t < 12$	$25 \le v_t < 50$	
27	Cruise/Acceleration	$12 \le VSP_t < 18$	$25 \le v_t < 50$	
28	Cruise/Acceleration	$18 \le VSP_t < 24$	$25 \le v_t < 50$	
29	Cruise/Acceleration	$24 \le VSP_t < 30$	$25 \le v_t < 50$	
30	Cruise/Acceleration	$30 \le VSP_t$	$25 \le v_t < 50$	
33	Cruise/Acceleration	$VSP_t < 6$	$50 \le {}_vt$	
35	Cruise/Acceleration	$6 \le VSP_t < 12$	$50 \le v_t$	
37	Cruise/Acceleration	$12 \le VSP_t < 18$	$50 \le v_t$	
38	Cruise/Acceleration	$18 \le VSP_t < 24$	$50 \le v_t$	
39	Cruise/Acceleration	$24 \le VSP_t < 30$	$50 \le {}_vt$	
40	Cruise/Acceleration	$30 \le VSP_t$	$50 \le v_t$	

Emission rates are estimated given the vehicle characteristics as well as fuel type utilization and meteorological conditions. For heavy-duty vehicles, rather than use VSP, scaled tractive power (STP) is used to reduce large variation from difference due to weight with coarsely defined operating modes. Instead of normalizing the vehicle's tractive power by its mass, a power scaling factor is used. Using STP_t, the heavy-duty vehicles follows the same implementation as for the light-duty vehicles in assigning operating mode and estimating emission rates. For off-road emissions production, such as idling and truck hoteling (extended idling by trucks), cold and hot starts, as well soak times, number of starts and hours operating off-road are considered in the calculation of emissions for a given vehicle.

To assess the impacts of automation and automated vehicles on the environment, it is necessary to first calculate the emissions and fuel consumption for a baseline scenario and then compare it to the emissions and fuel consumption for a scenario with a specified level of automation. In this way, benefit impacts can be identified.

4.4.2 Relationship to Other Parts of the Framework

Changes in other parts of the framework affect environmental impacts considerably. Notable relationships exist between the energy/environmental submodel and the vehicle mobility and economic analysis submodels (Figure 20).

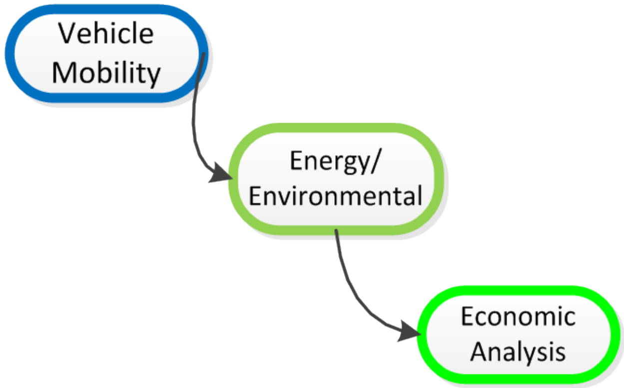

Figure 20. Relationship Between Energy/Environmental Submodel and the Rest of the Framework (Source U.S. DOT)

If safety improves (i.e., fewer incidents occur) then mobility can improve (less congestion), resulting in increased vehicle speeds along the roadway and decreased idling times and consequently, altered fuel consumption and emissions. If safety drives drive schedules rather than eco-friendly approaches, or if vehicles follow other vehicles at distances that allow for cars to improve aerodynamic characteristics, this too will directly affect fuel consumption and emissions. If accessibility improves, giving access to vehicles to a demographic previously limited, this might result in more vehicle miles traveled and more trips, impacting emissions. Furthermore, land use, transportation system usage and how people use automated vehicles and how automated vehicles affect transportation across all modes also will have environmental impacts. As a result, it is necessary to carefully consider several different scenarios within the feedback loop to assess the benefits and dis-benefits of automation and automated vehicles on energy and environment.

4.4.3 Inputs and Outputs

Emission rates in MOVES2014 are defined by a number of parameters that characterize road traffic, road conditions and driver behaviors. However, the parameters that are of most interest in this study are those that would be affected by the introduction of automation or automated vehicles into the system. For this reason, parameters such as road conditions and meteorological data, which are important in the emissions calculations, will not be discussed in detail, because the presence of automation or automated vehicles are not expected to change weather patterns or highway infrastructure. It should be noted that, within the analysis for these invariable parameters, (e.g., fuel composition, fuel ethanol content, vehicle age distribution, and meteorological data) default data within MOVES will be applied. This data is obtained by an initial run on the national scale to extract relevant default data. Where appropriate, this data will be modified for a given automation scenario to account for changes. Key input parameters that are expected to vary with vehicle automation include:

- Fleet composition
- Vehicle miles traveled (VMT)
- Speed
- Acceleration
- Vehicle-specific power (VSP)
- Idling times
- Off-roadway variables, such as cold starts and soak times

These parameters are informed through the feedback derived through the mobility analysis. Each of these inputs will be discussed in turn.

- Fleet composition – It is not anticipated that the fleet will vary dramatically but there is a possibility that vehicle replacement, vehicle type and fuel types may change with a heavier reliance on alternate fuel technologies, such as vehicle electrification. It is also possible that automated vehicles may be smaller and therefore lighter and more aerodynamic, which would contribute to alterations in the calculation of VSP.
- Vehicle miles traveled (VMT) – Automated vehicles have the potential to reduce or increase the number of vehicle trips and miles traveled, depending on the adoption of and practices for how automated vehicles are used.
- Speed and acceleration – Speed and acceleration, characterized by vehicle drive schedule, will be affected by automation on a first-order level and can be expected to alter operating mode assignment. Depending on the application and level of automation, there can a recognizable difference in average traffic speeds, the number of stops- and-go acceleration/deceleration movements.
- Vehicle-Specific Power – With a different speed and acceleration, as well as the potential for smaller mass and different aerodynamic characteristics of automated vehicles, it is expected that there will be a recognizable difference in calculated VSP, thus affecting operating mode assignment and estimated emissions.
- Idling times – Automation and automated vehicles can be expected to improve traffic dynamics, resulting in less time idling on roadways.
- Off-roadway vehicles – Cold starts and warm starts can potentially be changed with automated vehicles in car-sharing scenarios.

The MOVES analysis will yield the following metrics:

- Tailpipe carbon dioxide (CO_2) emissions (total, per capita, per vehicle-mile)
- Tailpipe criteria pollutant emissions (total, per capita, per vehicle-mile)
- Vehicle energy consumption
- Person energy consumption
- Total fossil energy consumption from highway transportation.

4.4.4 Data Sources

Speed and acceleration will be provided by a second-by-second drive schedule from the mobility analysis and serve as inputs into the calculation of vehicle-specific power. Fleet composition considerations will come from forecast data as well as MOVES default values that account for future fuel emission stringency requirements. Off-network considerations and idling times will be derived given the application and its calculated anticipated effects from the mobility analysis. Roadway data and infrastructure will be modeled for a given scenario and default data within MOVES will be used for meteorological data. Variables will be changed within the MOVES model according to reported data from literature and previous research.

4.4.5 Challenges

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

The MOVES2014 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 a lot of 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 MOVES2014 as a means of assessing environmental impacts may potentially miss some benefits. For instance, land use does not affect emissions or fuel consumption but can benefit air quality and can offset emissions production. Also, MOVES2014 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, transportation system usage and accessibility 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 to report trends and impacts.

4.4.6 Examples

Collision Avoidance: Collision avoidance will most likely see changes in drive schedule, speed, and acceleration. Depending on how the application works, it can have negative or positive environmental impacts. If collision avoidance puts safety as primary concern, then it can potentially have harder accelerations which would negative impact environment. On the other hand, if this requires larger following distance to avoid collisions then we potentially could see smoother drive and reduced emissions.

Traffic Jam Assistance: This application will most likely see changes in drive schedule, speed, acceleration, and idling time. It can have negative or positive environmental impacts. Less idling time will reduce emissions. However, rerouting to avoid traffic may result in longer vehicle miles traveled or to roads that have lower speeds with higher emission rates. The benefits of this application are uncertain.

Cooperative Adaptive Cruise Control: Cooperative adaptive cruise control will most likely see changes in drive schedule, speed, acceleration, and idling time. Depending on how the application works, it can have negative or positive environmental impacts. Closer following distances might improve aerodynamics (seen more in platooning) but will require harder accelerations. Larger following distances could result in smoother drives. And again, faster speeds for this application’s use could also impact emissions.

Platooning: Platooning will most likely invoke changes in drive schedule, speed, acceleration, and aerodynamics. Platooning has already been shown in the literature to reduce fuel consumption in heavy-duty trucks and has fuel savings benefits for following vehicles as well as the lead vehicle. For an environmental analysis, each vehicle in a platoon experiences different benefits which would require separate analysis because of varying fuel savings depending on vehicle rank. The impact from platooning is hard to determine in MOVES because of averages in default values and requires more specifics for aerodynamic drag terms to fully capture this scenario.

Full Automation in a Controlled Environment: Full automation in a controlled environment will most likely see changes in drive schedule, speed, acceleration, aerodynamics, fleet composition, vehicle miles traveled, cold starts, and idling. An increase in VMT can increase emissions. Increases in speeds will impact emissions, although for positive or negative, would depend on what speeds are increased to. Shared-vehicle system could result in less cold starts which would reduce emissions. Overall, it is anticipated that there would be less idling. Also, fleet composition might be newer, resulting in emissions reductions.

4.4.7 Regional and National Modeling

MOVES2014 is capable of working at a microscale for one vehicle or for a fleet of vehicles on a link or multiple links in a highway system (regional) as well as on a national scale. The considerations and implementation for a regional and national model is similar as for a single vehicle, with complexity added with each additional link in the system, to account for the increase in vehicle miles traveled on various road types. Data from the Highway Performance Monitoring System, which provides all roadway information across the United States, supplies the information on roadway type and roadway lengths to scale the project to regional or national emission and fuel consumption estimates.

4.5 Transportation System Usage

4.5.1 Description of the Approach

For the past 50 years, Metropolitan Planning Organizations (MPOs) and State DOTs have been using quantitative travel forecasting models for long range planning and program evaluation. We propose to build upon the substantial work that has already been done in this area over several decades. (TRB Special Report 288, 2007) provides additional information on current practice and future direction in metropolitan travel forecasting.

Assumptions typically made in modeling include the following:

- A region is divided into discrete zones, with groups of travelers being modeled. These zones are often based on census tracts; each might have a population of a few thousand. (Note that in state-of-the-art parcel-level modeling, this assumption is relaxed, and individual synthesized travelers are modeled).
- Travel is the result of sequential decisions (although there may be feedback loops) ranging from the long term decisions of home and workplace location, to the very short term decisions of route choice. The traditional four-step process includes
    - Trip generation (how many trips come out or go into a particular zone?)
    - Trip distribution (what are the origin and destination zones?)
    - Mode choice (do I drive or use transit?)
    - Route choice (what route do I take?)
- Most models focus on daily trip patterns on a weekday. Long distance trips, freight, and weekend travel might not be modeled.
- Trip types are usually enumerated. They may include work/school (the daily commute), shopping/other, and escort trips (e.g., taking a child to school).
- Travel modes are usually enumerated. They may include single-occupant auto, various types of carpools, transit, transit with auto access (either park & ride or kiss & ride), and sometimes walking and bicycling. In some implementations (typically, in smaller metropolitan areas), only the auto travel mode is considered.
- Automobiles are assumed to be associated (owned or leased) with a household.
- The disutility of travel includes travel time (people prefer shorter trips), out-of-pocket cost (parking, tolls), and a mode-specific constant relating to other attributes (such as comfort) of the chosen mode. In mode and route choice, travelers seek to maximize utility (or, minimize disutility).

- In route choice, travelers seek to minimize their own travel costs (travel time, out of pocket cost), even though the end result may not be optimal from a system standpoint.
- Safety is not explicitly modeled. Rather, if a particular mode is viewed as unsafe or otherwise unpleasant, it might have a less favorable mode-specific constant, which will tend to penalize that mode in demand modeling.

The traditional four-step process remains in use at many MPOs, and has been used to analyze major transportation infrastructure and policy decisions. This approach separates the phases of trip generation, trip distribution, mode choice and assignment into four sequential steps. It typically deals with average conditions, for example, the "typical" morning peak, midday, and evening peak weekday travel patterns. At the time the four-step model was developed, computer capabilities were far less than what they are today, and some data sources (such as probe vehicle information from mobile phones and toll tags) did not exist. Because traditional models deal with average conditions and treat travel as a series of sequential decisions, they have difficulty addressing a number of areas, including:

- Variable road pricing
- Ramp metering
- Traveler information strategies;
- Reversible lanes, variable speed limits, and other dynamic transportation management strategies;
- Policies affecting travel scheduling such as parking pricing, transit pricing and flexible work schedules, reversible lanes, high occupancy vehicle lanes and high occupancy toll lanes
- Work and shop-at-home situations; and
- Bottleneck improvements.

NCHRP Synthesis 406 "Advanced Practices in Travel Forecasting," (2010), presents several of the recent advances in travel forecasting. Similar to the traditional approach, a chain of models at varying time scales are used. At the top are the long-term (years) models of land use (home and work place) and vehicle ownership. At the bottom are the minute-by-minute route choice decisions. Although many types of models could be called "advanced models," we will consider the state-of-the-art to be a combination of regional Activity-Based Models and Dynamic Traffic Assignment models.

In an activity-based model (ABM), persons in households are modeled as engaging in activities (at home, at work, shopping, school, etc.), with travel as a derived demand arising from those activities. Travel in such models is viewed as tours for persons in a household, where the individual trips (legs of a tour) depend upon other parts of the tour. Furthermore, joint travel (e.g., a parent bringing a child to soccer practice) is explicitly modeled. Activity based models provide the following capabilities that don't exist in traditional four-step models:

- The ability to incorporate scheduling into a traveler's decision process. Maintaining time and space constraints on travelers is a significant aspect of activity based travel demand models.
- The ability to evaluate chained trips, or tours, that travelers take over the course of a day, where the decisions made for the first leg (for example, whether to drive or take transit), influence the mode choice and schedule options that are available on subsequent legs.

Dynamic traffic assignment (DTA) models treat the road network at a greater level of detail than done for the static assignment model, but at less detail than for a typical engineering-focused, traffic simulation model. Dynamic traffic assignment models provide the following capabilities not available in traditional four-step models:

- Travel time and costs are represented with more time detail, typically 15 minutes or less, providing a more accurate representation of traffic conditions for a given scenario;

- Traffic controls and intersections are represented with more detail, providing a more accurate representation of traffic operations for a given scenario;
- Traffic flows and queues are represented with more spatial and time detail, allowing the modeled traffic flows to better correspond to changes in congestion, costs, traffic controls, and intersection geometry.

The combination of ABM and DTA provides a fine-grained time-of-day model sensitive to traffic operations and traveler schedule behaviors. Because of these additional capabilities, joint ABM /DTA models have the potential to provide insights not available from traditional four-step models. For further information on these models, please see (Castiglione, Bradley, & Gliebe, 2015) and (Chiu, et al., 2009).

Figure 21 illustrates a generic ABM-DTA framework, with household decisions ranging in timeframe from years to minutes. Not shown in the figure are the feedback loops. For example, a household that is able to make effective use of transit in the near term might be less inclined to buy a new car in the long term.

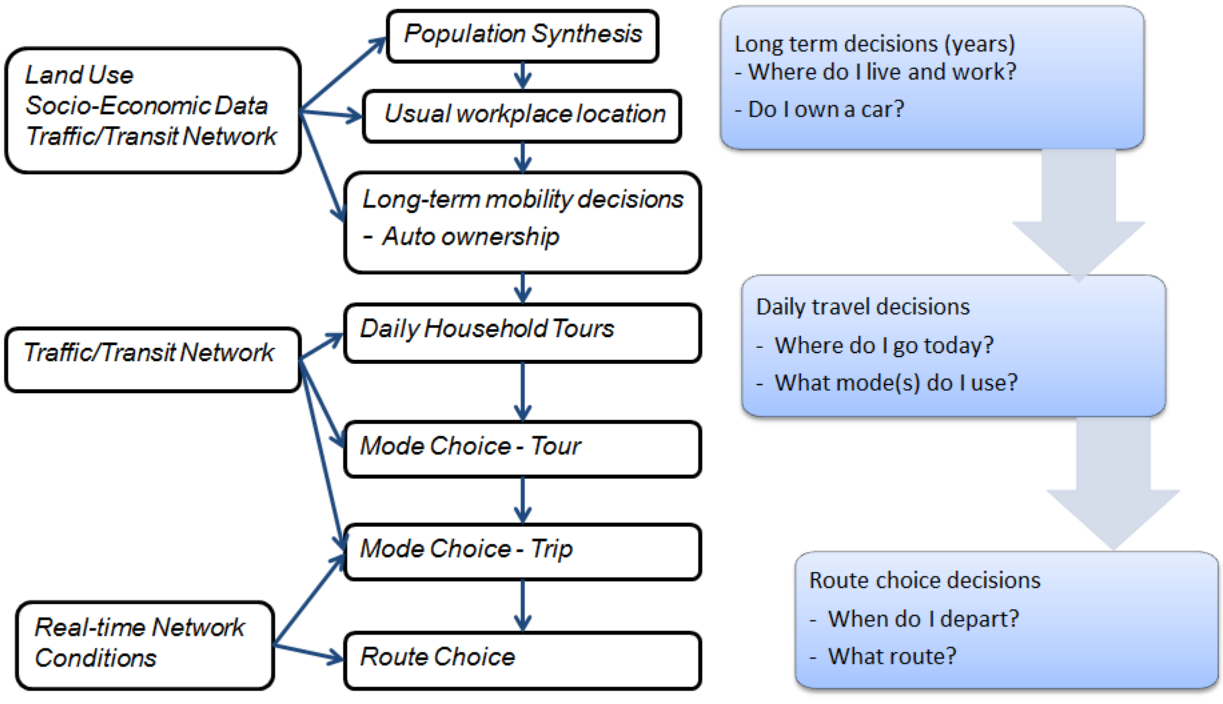

Figure 21. Activity Based Modeling Framework (Source: U.S. DOT)

The presence of automation, particularly at the higher levels, will influence both transportation network capacity (travel "supply") and the demand for travel, as illustrated in Figure 22.

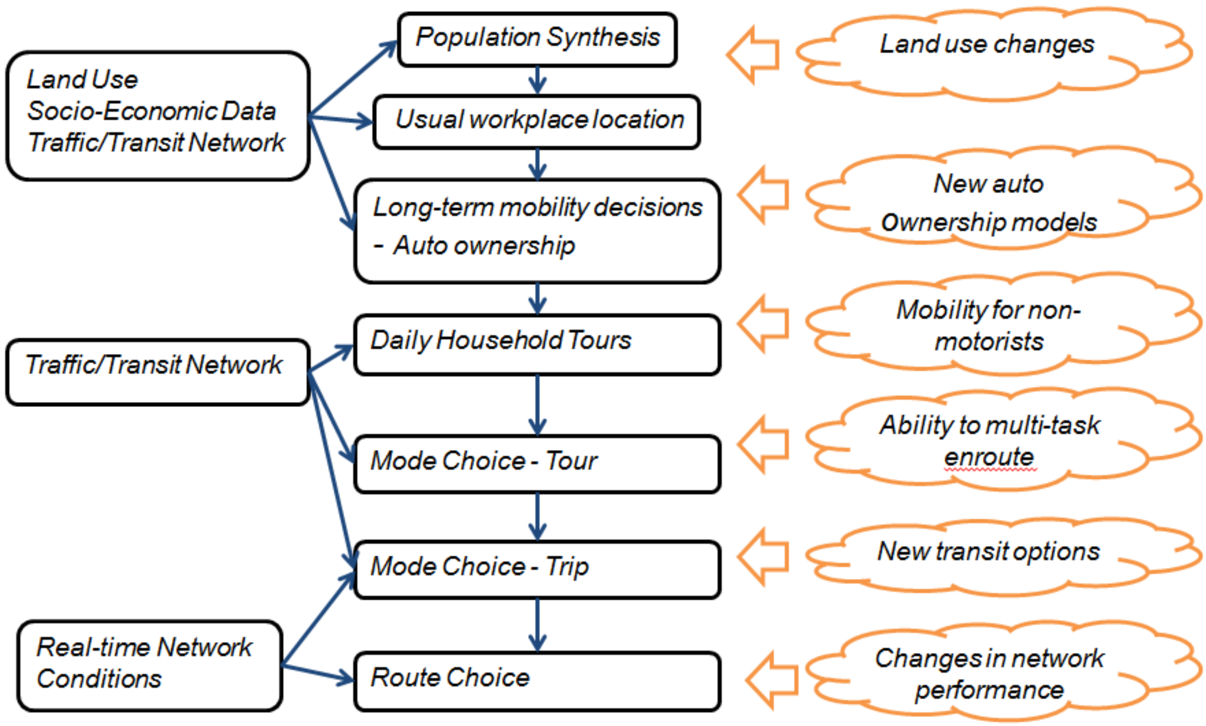

Figure 22. Impacts of Automation on Planning Models (Source U.S. DOT)

The proposed approach is to use the existing travel demand modeling framework as much as possible, while addressing the changes that automation will bring. These changes are discussed further in section 4.5.4 .

4.5.2 Relationship to Other Parts of the Framework

Changes in transportation system usage drive much of the feedback in the modeling framework (Figure 23).

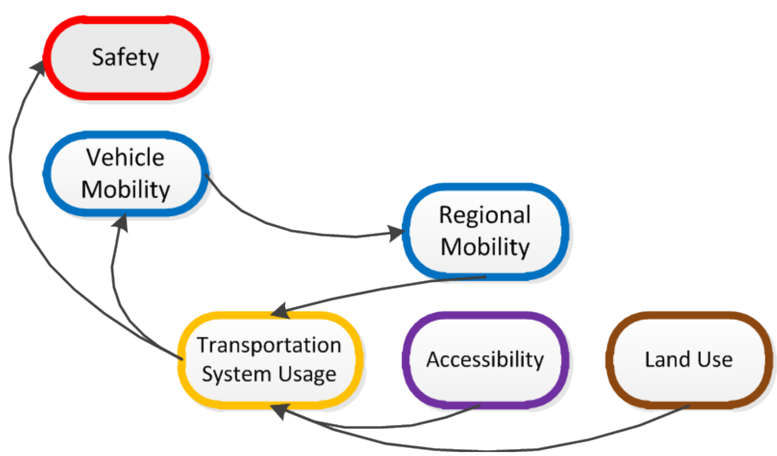

Figure 23. Relationships Between the Transportation System Usage Submodel and the Rest of the Framework (Source U.S. DOT)

If regional mobility or accessibility improve (either through less congestion, or the driving task becoming less onerous), there will be more usage of the modes that have improved. Similarly, if land development becomes more dispersed, there will be more travel. On the other hand, if land use becomes more concentrated (perhaps due to reduced parking requirements), the need for travel might be reduced.

Changes in transportation usage influence mobility and safety. If there is more travel, there will likely be more congestion and more crashes.

4.5.3 Inputs, Outputs, and Data Sources

Data needed for activity-based modeling include land use and demographic information, household survey data, and transportation network data.

Current land use information may be gathered at spatial resolutions ranging from a transportation analysis zone (TAZ) down to the parcel level. Basic population and employment data at the block level (intermediate between a TAZ and a parcel) are available from the U.S. Census.

Demographic information includes synthetic household and person-records that represent the socio-economic characteristics of households and persons in an area. These characteristics, from (Castiglione, Bradley, & Gliebe, 2015), may include

- Household size
- Household composition and life cycle (e.g., age of householder by presence of own children)
- Number of workers per household
- Household income category
- Age and gender of each person
- Employment and student status of each person.

Auto ownership is an output of the long-term auto-ownership model, and then becomes an input to the daily household tour model.

Household survey data includes the actual trip patterns of a sample of households in a region and is used to assemble the tours, including joint-travel decisions. Analysis of the survey data and observed travel patterns will help to reveal:

- Attitudes towards varying land uses (e.g., the tradeoff between a big house far away and a smaller house closer to work), as revealed by actual land use decisions.
- Attitudes towards vehicle ownership, as revealed by actual vehicle ownership patterns.
- Demand for travel, typically categorized by trip purpose (work, school, shopping, etc.).
- Household and personal utility functions for travel, including the value of time and the value of reliability.

Transportation network data includes both highway and transit networks. It is used to generate travel times and costs between origins and destinations. The network typically includes

- Major roads (freeways, arterials, and some collectors) in a region with attributes such as number of lanes, free flow speed, hourly capacity, and tolls (if any). Some networks may also include parking cost information, as well as capacity and delay information at specific intersections.
- Transit services including type of vehicle and schedule information.
- A means to connect the origins and destinations for trips to the network.

Outputs include trips on each link, and between each origin and destination, by time of day. They may include total trips, travel distance, travel time, and average trip duration and speed. From these, various congestion indices may be calculated. Accessibility measures may also be calculated.

Because of the long history of travel demand model development, much of this data are available, although, due to its expense, household survey data is often less extensive than desired. Also, the transportation network may not include enough detail to enable simulation modeling without gathering additional information, such as signal timings and turning lane configurations, about the network.

4.5.4 Challenges

Regional modeling is often discussed in terms of the “demand side” (e.g., the demand for travel, and how it is influenced) and the “supply side” (e.g., the capacity of the transportation network). Supply-side gaps, such as understanding the effect of automated vehicles (AVs) on traffic flow, were discussed earlier, so the following discussion will focus on the demand-side. Significant issues include the following:

- First is the fundamental question of user acceptance of AVs, particularly at the higher levels of automation where the driver cedes all control. Will travelers be interested in buying such vehicles? What benefit will they see in the automation features?
- What will the impacts of AVs be on land use? This question has several dimensions. One might envision planned residential communities or large office parks that are designed to have their transportation needs met by AVs. Will households and corporate decision-makers embrace such communities when considering where to locate the home or workplace? If vehicles are able to park themselves at remote locations, will that enable higher density land uses, which would make walking more attractive? Furthermore, if vehicles can park themselves, the amount of space required for parking may be significantly reduced. On the other hand, if the commute to work becomes less onerous, would that encourage sprawl, with longer commute trips?
- What will happen with vehicle ownership? Currently, shared vehicles are located near transit or in major residential and employment areas, because their users typically need to walk, bike or use transit in order to reach them. If a shared vehicle can deliver itself to a user’s doorstep, the use of shared vehicles may become much more attractive.
- If non-motorists are able to make single-occupant car trips, what will that mean for travel demand?
- What will happen with ride sharing? The reduction in labor costs with automated transit vehicles may blur the distinction between public transit and taxi services, whereby it becomes economically feasible to have small (4 – 8 passenger) transit vehicles, on either fixed or variable routes.
- Finally, what will happen to the disutility of travel with increased automation? Will travelers no longer view long commutes as onerous, because they are now able to engage in other activities?

Research aimed at closing these gaps is still in its infancy. A few papers were presented at the 2014 Automated Vehicle Symposium. More recently, modelers from the Puget Sound Regional Council began to explore the potential impacts of AVs in the Seattle region. They state that “Travel models will need to have major improvements in the coming years, especially with regard to shared-ride, taxi modes, and the effect of multitasking opportunities, to better anticipate the arrival of this technology.” (Childress, Nichols, Charlton, & Coe, 2015)

To show how some of these challenges might be addressed, consider several technological scenarios:

- Level 1–2 automation, with a human driver, but vehicles can use certain roads more efficiently (e.g., platooning).
- Level 3 automation on selected roads.
- Level 4 automation (driverless) in a controlled, low-speed environment with shared vehicles (neighborhood shuttle).
- Level 4 automation (driverless) in a controlled, low-speed environment with owned vehicles (self-parking).

4.5.4.1 Level 1-2 Automation

We imagine that a driver still needs to be in each vehicle, but there may be platooning on certain roads, with a substantially higher lane capacity than what exists now. This can be modeled as an incremental change on existing model structures, as follows:

- A new vehicle type (platooning-capable) will need to be modeled.
- A new lane type (platooning-enabled) may need to be created for certain roads.
- Tours that use the new vehicle type will need to be forecast.
- Volume / speed functions will need to be developed that consider the new vehicle at varying levels of market penetration, both for the new platooning-capable lane, and for transitions to and from that lane.

To summarize, Level 1-2 automation may affect network capacity, but will not affect the disutility of travel. If network capacity increases, reducing congestion, there may be increased demand for travel in response.

Research needs for modeling this level of automation include two primary areas:

- Understanding the effect of platoon-capable vehicles on traffic flow, both in dedicated lanes and in mixed traffic.
- Forecasting the market diffusion of such vehicles.

4.5.4.2 Level 3 Automation on Certain Roads

This is similar to the Level 1-2 automation discussed earlier in that a driver still needs to be in each vehicle, ready to take over in some amount of time. However, the driver may disengage from the driving task for substantial amounts of time. Changes in existing model structures will include the following

- The changes listed in Level 1-2 Automation, above, plus
- The disutility of driving will be reduced by some amount for certain vehicles and road segments.

This level of automation is likely to affect both network capacity and the disutility of travel.

In addition to those listed under Level 1-2 Automation, research needs include the following:

- Understanding the human factors issues in Level 3 automation: can it be done safely? What amount of time is needed for driver re-engagement?
- Understanding the value to drivers of Level 3 automation: will the ability to multi-task make longer commutes more attractive?

4.5.4.3 Level 4 Automation in Selected Low-Speed Environments with Shared Vehicles

This is the low-speed neighborhood shuttle that would provide service for short trips, or may enhance access to existing transit lines. It might be modeled as a taxi or demand-responsive transit service. Characteristics of the service that would need to be modeled include

- Coverage area – what trips are served?
- Travel time for trips.
- Average and maximum wait time.
- Out of pocket cost.
- The convenience and comfort of calling the vehicle, waiting, and traveling on the vehicle.

In the long-term, such services may lead to changes in land use, if neighborhoods are built or retrofitted with low-speed, automated vehicles in mind.

4.5.4.4 Level 4 Automation in Selected Low-Speed Environments with Owned Vehicles

In this case, a person's owned vehicle has limited self-driving capabilities, which are primarily used for parking, either at the driver's destination, or at a more remote location. A driver might exit the vehicle at the entrance to a parking garage; the vehicle would then find a parking space in the garage and park itself. At one level, this could be modeled as simply reducing the generalized-cost (out-of-pocket cost plus walking time) of parking. However, there are several additional far reaching impacts:

- With vehicles parking themselves, less space is required, as there is no need for the driver to open the door to exit the car. Also, with automation, maneuvering may be more precise.
- Parking no longer needs to be located near the driver's destination. The removal of parking at the driver's destination may enable higher density land use, making walking a more attractive option for local trips within the business district.
- Even limited self-driving capabilities may make car-sharing more attractive. A limitation of current car-sharing is that the vehicles generally need to be located either at a transit stop or within walking distance of their users. If the vehicles can deliver themselves, car-sharing may become more attractive to many potential users.

Challenges include quantifying the following impacts:

- More convenient parking.
- Land use changes with remote parking.
- The market for car sharing.

With remote parking, a new trip type may need to be modeled: the parking trip. There might be an analogy with an escort child-to-school trip. With the escort trip, the parent takes the child to school, and then takes the car to some other destination. With the parking trip, the car takes its driver to a destination; then the car takes itself to a parking space.

4.6 Accessibility

4.6.1 Description of the Approach

As described in section 2.4, accessibility can be measured in a number of ways. For the purposes of this modeling framework, we will consider accessibility on a regional scale. A variety of methods for analyzing regional accessibility can be found in the literature. We will explore these options to determine which are most appropriate. Some examples are discussed below.

Isochronic or Cumulative Opportunity

This approach counts the number of potential opportunities that can be reached in a predetermined travel time. This measure is easily interpreted, but does not account for people's actual choice in residence or employment location (El-Geneidy & Levinson, 2006). This approach is given by:

$$A_i = \sum_j B_j a_j$$

Where

A_j	Accessibility measured at point *i* to potential activity in zone *j*
A_j	Opportunities in zone *j*
B_j	A binary value equal to 1 if zone *j* is within a predetermined threshold and 0 otherwise

Gravity-based

This widely used measure estimates the cost to move between origin and destination for various opportunities. The need to develop an impedance factor is a disadvantage of using this method. It is also difficult to use when considering multimodal trips (El-Geneidy & Levinson, 2006). This approach is given by:

$$A_{im} = \sum_j O_j \, f(C_{ijm})$$

$$A_{im} = \sum_j O_j \, (C_{ijm})^{-2}$$

$$A_{im} = \sum_j O_j \, \exp(\theta \, C_{ijm})$$

Where

A_{im}	Accessibility at point *i* to potential activity at point *j* using mode *m*
O_j	Opportunities at point *j*
$f(C_{ijm})$	The impedance or cost function to travel between *i* and *j* using mode *m*
$\exp(\theta \, C_{ijm})$	Negative exponential function to travel between *i* and *j* using mode *m*

Geographic Information Systems (GIS) Mapping

Some agencies have used GIS to analyze accessibility regionally. Network distances can be mapped between various origins and destinations to determine how many destinations are within a certain distance or travel time period from the origin. The City of Portland uses GIS in this way to determine the number of services within a 20-minute walk of residences.[37]

4.6.2 Relationship to Other Parts of the Framework

Figure 24 illustrates the relationships between accessibility and other parts of the framework.

[37] http://www.portlandonline.com/portlandplan/index.cfm?a=288098&c=52256

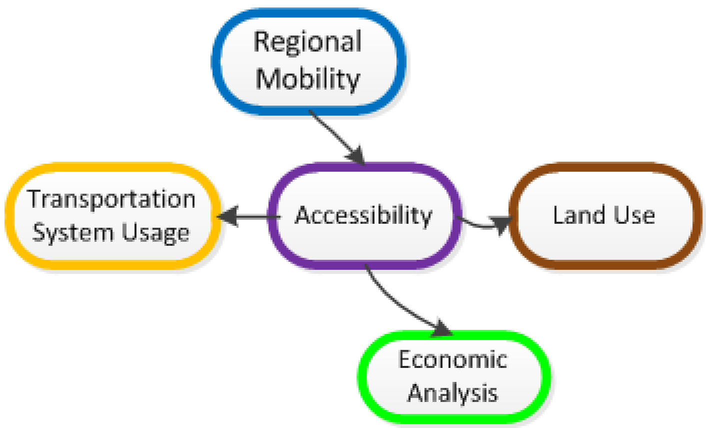

Figure 24. Relationships Between the Accessibility Submodel and the Rest of the Framework (Source: U.S. DOT)

Accessibility is very closely related to and affected by mobility. Faster travel times, or increased mobility, can also increase accessibility by expanding the area that a user can travel to within a certain time period. Conversely congestion, or decreased mobility, can limit accessibility by reducing the area that a user can travel to in a certain time period. Improvements to the accessibility or mobility of one mode may have deleterious impacts on the accessibility or mobility of another. For example, increased motor vehicle speeds on a corridor may make bicycling appear more dangerous and cause a bicycle user to choose a longer but safer route.

The availability of transportation options is a component of accessibility that relates directly to transportation system usage. Given a viable option for travel, some trips that were previously too difficult, time-consuming, dangerous, stressful, etc. may be taken, thereby increasing the overall number of trips in the system. For example, system users who are unable to drive may not take certain trips because there is no viable option for doing so. Highly automated vehicles have the potential to create a viable option in these cases.

Another important component of accessibility is access to jobs. Creating a system that is more efficient or reaches areas that it did not reach before may create new access to employment for system users. This can result in economic benefits for a whole community. Automated vehicles have the potential to reach low-income communities with poor public transportation service and low rates of vehicle ownership, allowing them to access more opportunities, including jobs and medical treatment.

Access to transportation options and to goods and services is strongly influenced by development patterns and land use. For example, large block sizes and low-density development do not easily support fixed-route public transit, as they create an environment where opportunities are spread far apart from one another and central locations that make for effective transit stops are nonexistent. Indeed, the relationship is bi-directional—the development of a transit hub is likely to spur commercial development as well. In the context of automated vehicles, improvements in accessibility will partially depend on any changes in land-use patterns that result from potentially significant increases in mobility. All other things being equal, improvements in transportation – such as those from automated vehicles—would affect location choice by reducing the generalized costs of travel and thus increasing the desirability of peripheral locations relative to those in the center. There has been some discussion more specifically on the potential for automated vehicles to reduce urban parking needs, since a shared fleet of fully automated, self-repositioning vehicles could replace a significant portion of the current vehicle fleet (Fagnant & Kockelman, 2014). Even without vehicle sharing, the ability of vehicles to self-park in much tighter spaces (or even bumper-to-bumper) would reduce the space needs of parking facilities.

Either of these developments would have the effect of freeing up land currently used for parking lots and garages to be redeveloped into residential or commercial space, increasing urban densities.

4.6.3 Inputs and Outputs

Most approaches to measuring accessibility require similar data, including the number of people residing and working in each transportation analysis zone (TAZ); demographic data, such as household size, composition, and income; road, transit, and bicycle/pedestrian networks; traffic counts; land use; mode split; and growth/development trends.

Outputs will include measures such as:

- Average wait for shared vehicle
- Percentage of people within x-minutes of major activity (employment, medical, etc.)
- Average commute distance
- Effective system capacity

4.6.4 Data Sources

Many of the datasets described above are typically included in planning models; however, to more accurately estimate impacts on non-motorists a special consideration will be given here for modes that don't involve driving, such as transit, walking, and bicycling. Household travel surveys and datasets from the U.S. Census Bureau will provide helpful demographic and travel behavior data.

4.6.5 Challenges

Fully automated vehicles that require no human driver could have far-reaching impacts on accessibility, particularly for those who are unable to drive. New transit options in the form of shared automated taxi-like vehicles could create a highly efficient system of on-demand transit that provides door-to-door service. The cost of on-demand, door-to-door personal transit may decline dramatically from what it is today (modern taxis), making it an affordable option for many more travelers. This could drastically increase the number and breadth of opportunities accessible to low-income, elderly, and disabled travelers by easing travel costs and reducing travel time compared to traditional public transportation. Such improvements in access and coupled with the changes in nature of the transportation system as a whole could have significant long-term impacts of land use. As described above, easing the monetary and time cost of travel for a broad range of travelers could remove the disutility of long commuting trips, thus encouraging sprawling, decentralized development. On the other hand, highly automated vehicles that are able to drive themselves and are most efficient when constantly shuttling travelers do not need to park for long periods of time, or perhaps at all. This could substantially reduce the need for surface parking. In addition, automated parking applications will require less space per vehicle. Understanding the range of these impacts and how to consider them in the model will be a challenge as the possible direction and magnitude of the impacts likely depend on policy decisions that govern land use and the cost of travel.

Effects on certain sectors of industry are also worth considering and vary depending on policy decisions. Taxis and public transportation in their current form may become less desirable to the traveling public. The nature of the service provided by these industries may be forced to adapt to the new demands brought forth by the advantage that automated vehicles create.

4.7 Economic Benefits

Figure 25 shows the relationships between the economic analysis submodel and the rest of the framework.

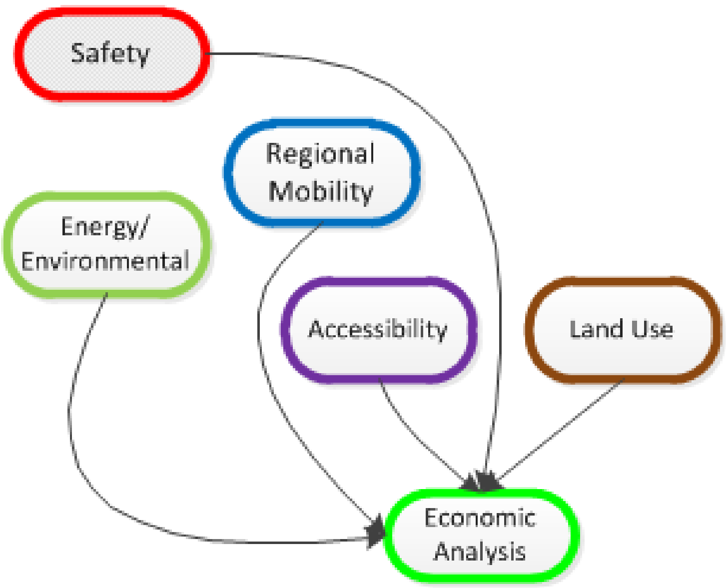

Figure 25. Relationship Between the Economic Analysis Submodel and the Rest of the Framework (Source: U.S. DOT)

Economic modeling is planned as a follow-on to the other modeling efforts, as described above. The long-term macroeconomic impacts of automation are expected to arise as logical consequences of the key impacts identified in other modeling processes, such as avoided injuries (safety) and travel time savings (mobility). Although the economic component, therefore, depends on the completion of the other analyses, it is possible to sketch out the broad outlines of the proposed macroeconomic modeling approach here. The key to this approach is establishing and quantifying linkages between the estimated safety, mobility, and other impacts of automation, on the one hand, and determinants of economic growth on the other hand—namely labor, capital, and total factor productivity.

One example is that a portion of the travel-time savings that is estimated to arise from automated vehicle operation may be used for additional time in paid employment, thereby increasing labor supply and overall output. Likewise, lower transportation costs and greater options for non-drivers may also increase labor supply by reducing the generalized costs of commuting and eliminating barriers to transportation. These impacts will be analyzed using a Computable General Equilibrium (CGE) model of the U.S. economy that has been previously used for estimating the economic impacts of highway investments.[38] CGE models are models of the national economy grounded in detailed data tables that estimate the overall flow of transactions across different parts of the economy. The CGE model incorporates dynamic economic adjustment processes, and

[38] The specific model, USAGE-Hwy, is a variant of the United States Applied General Equilibrium Model (USAGE) that has been adapted for analysis of highway projects. See Puckett, S., et al., "Computable General Equilibrium Analysis of the Macroeconomic Impacts of Highway Investment in the United States: Application of the USAGE-Hwy Model," forthcoming in Proceedings of 94th Annual Meeting (2015), Transportation Research Board, Washington, DC.

thus can be used to estimate how certain external changes, such as increased labor force participation, would ripple through the U.S. economy and change output and price levels. The model can also be used to analyze the more direct impacts of the automation investments themselves.

This approach will require a set of inputs related to changes in labor force participation, hours worked, and other economic variables. These inputs are related to, but not directly provided by, the outcomes of the planned modeling efforts for the safety, mobility, and other impacts of automation. An intermediate step will be required to translate modeling outcomes into economic terms. For example, estimates of injuries avoided and hours of travel time savings will need to be converted into forecasts of changes in hours worked. This step may require reference to labor-market models, survey data, and/or observational studies.

Full, Level-4, or Level-5 automation offers the prospect of significant cost savings, new paradigms for passenger and freight travel, and potential changes in major sectors of the economy. These types of impacts are inherently more speculative and are more difficult to model, and they are largely beyond the scope of the current effort. To some extent they can be addressed qualitatively with reference to metrics such as vehicle ownership, transportation affordability, freight costs, and employment. However, the CGE model is not designed to answer detailed sector-specific questions, such as whether automated safety systems would permit major changes to vehicle designs, and the implications for weight and cost. Land use impacts will also depend strongly on state and local decision-making, for example in planning and zoning, which are difficult to model or forecast on a national scale.

4.8 Land Use

Figure 26 shows the relationship between the land use submodel and the rest of the framework.

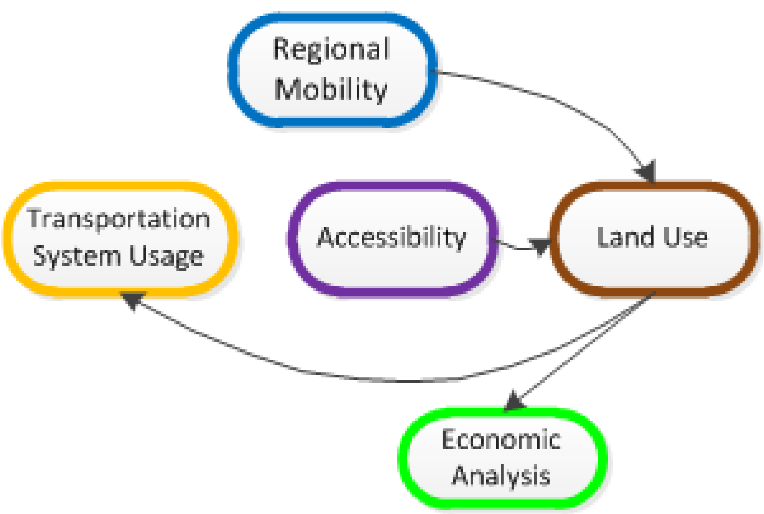

Figure 26. Relationship Between the Land Use Submodel and the Rest of the Framework (Source: U.S. DOT)

Transportation and land use are highly intertwined. Personal transportation choices such as VMT levels and mode choice are strongly influenced by development patterns, and much of the urban landscape is devoted to accommodating transport functions such as car parking, streets, highways, and transit systems. As such, widespread adoption of automated vehicles, particularly at higher levels of automation could have significant impacts on future land use.

Location choice theory holds that households and businesses make tradeoffs between transportation costs, rent costs, space needs, and access to the economic activities of the urban center, including employment, shopping, amenities, and proximity to customers and suppliers. As a result, most metropolitan areas feature a rent gradient, with land costs per square foot highest near the downtown core, and declining as one moves away from the center due to the higher transportation costs of accessing the center.

All other things being equal, improvements in transportation—such as those from automated vehicles—would affect location choice by reducing the generalized costs of travel and thus increasing the desirability of peripheral locations relative to those in the center. Historically, this pattern can be seen in the U.S. with the successive rounds of suburbanization that followed the advent of commuter railroads, trolley services, and the automobile. For automated vehicles specifically, it has been suggested that the potentially higher speeds and reduced congestion, along with greater flexibility to work or relax while in transit, would lead to even greater decentralization in the U.S. metro areas (Laberteaux, 2014); with similar conclusions from (Beimborn, 1996).

At the same time, land use impacts can be difficult to predict and are sometimes counterintuitive. To take one example, although recent advances in information technology and telecommunications arguably make central physical locations much less important than in earlier eras, many large US cities have seen substantial rebounds in population since the 1970s. The financial services and software industries, whose products are largely virtual, also remain highly geographically concentrated in a few areas such as Wall Street and Silicon Valley.

There has been some discussion more specifically of the potential for automated vehicles to reduce urban parking needs, since a shared fleet of fully automated, self-repositioning vehicles could replace a significant portion of the current vehicle fleet. (Fagnant & Kockelman 2014). Even without vehicle sharing, the ability of vehicles to self-park in much tighter spaces (or even bumper-to-bumper) would reduce the space needs of parking facilities. Either of these developments would have the effect of freeing up land currently used for parking lots and garages to be redeveloped into residential or commercial space, increasing urban densities.

Metropolitan planning organizations are enhancing their modeling capabilities with regard to the interaction between transportation and land use. However, forecasting land use changes remains challenging due to the many factors that influence location choice and the mediating influences of geographic constraints, demographics, personal values and tastes, and other factors. Changes in land use also take much longer to unfold because of the legacy of existing settlement patterns and infrastructure and the relatively high costs of relocation. Moreover, land use patterns are also governed by local planning and zoning policies that can strongly shape future growth, though the level of government intervention in the market varies from place to place.

Overall, the impacts of automation on land use are beyond the scope of the initial analysis and will continue to present analytical challenges for some time. However, some understanding of the potential mechanisms for land use changes is important, especially since land use will, in turn, have longer-term influences on travel demand, emissions, and other impacts studied here.

Chapter 5 Next Steps

During the development of this framework, we have received valuable input from various stakeholders. To ensure these relationships are maintained moving forward, following the acceptance of this initial framework, we will seek to form partnerships both within U.S. DOT and with transportation professionals in academia and industry. Through these partnerships we hope to gain valuable input on our approach and findings, and leverage existing expertise and tools to conduct the analysis. These partnerships will also help to build consensus with the analytical approach and thereby foster greater acceptance of the findings.

Concurrent to the formation of partnerships, we will identify the primary data sources and assumptions, and define the specific scenarios that will be analyzed in an initial iteration of an AV benefits model. Taken together, this information will define the scope of our overall analytical model, and thereby the requirements of each submodel (e.g., mobility, safety, etc.). To finalize this planning phase of model development, we will develop a report that lists our data sources, the justification of our assumptions, and defines the scope statement of the model.

Upon acceptance of our model's scope statement, we will develop or obtain access to the necessary modeling tools. While some of these models may already be accessible to our team, or are commercially available, we believe that some models will need to be developed or adjusted either through in-house resources or a third-party partnership. Initially our focus will be on the development of the safety and mobility models, followed immediately by the energy and environmental model. We have chosen this stepwise approach to minimize interface/compatibility issues between the models, and to reduce the timeframe for communicating our findings. Furthermore, by starting with these models, we will have the opportunity to compare/validate our results against previously published research findings, particularly for lower levels of automation such as CACC. Further iterations of the model will incorporate additional scenarios and demonstrate the impacts from the other submodels on regional transportation usage and land use.

For each iteration of the model, we will develop a report that includes a description of the tools and methods, a summary of findings, a comparison to previously reported data (where applicable), and lessons learned to improve the performance of future models.

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Appendix A. List of Acronyms

Abbreviation	Term
ABM	Activity Based Modeling
ACC	Adaptive Cruise Control
AERIS	Applications for the Environment: Real-time Information Synthesis
AV	Automated Vehicle
AVSS	Active Vehicle Safety System
BTU	British Thermal Unit
CACC	Cooperative Adaptive Cruise Control
CAFE	Corporate Average Fuel Economy
CAMP	Collision Avoidance Metrics Partnership
CO_2	Carbon Dioxide
CNG	Compressed Natural Gas
DOT	Department of Transportation
DSRC	Dedicated Short-Range Communication
DTA	Dynamic Traffic Assignment
EPA	Environmental Protection Agency
EU	European Union
FARS	Fatality Analysis Reporting System
FCA(T)	Forward Collision Avoidance (Technology)
FCW	Forward Collision Warning
FHWA	Federal Highway Administration
GES	General Estimates System
GHG	Greenhouse Gas
GPS	Global Positioning System
IIHS	Insurance Institute for Highway Safety
ITS JPO	Intelligent Transportation Systems Joint Program Office
LOS	Level of Service
LNG	Liquefied Natural Gas
MAIS	Maximum Abbreviated Injury Scale
MOVES	Motor Vehicle Emission Simulator
MPO	Metropolitan Planning Organization
NCHRP	National Cooperative Highway Research Program
NHTSA	National Highway Traffic Safety Administration
OEM	Original Equipment Manufacturer
PMT	Person Miles Traveled
RDE	Research Data Exchange
SAE	Society of Automotive Engineers
SIM	Safety Impact Methodology
TAZ	Transportation (or traffic) Analysis Zone
TFHRC	Turner Fairbank Highway Research Center

Abbreviation	Term
TRB	Transportation Research Board
TTI	Texas Transportation Institute
U.S. DOT	United States Department of Transportation
V2I	Vehicle-to-infrastructure
V2P	Vehicle-to-person (pedestrian or bicyclist)
V2V	Vehicle-to-vehicle
VMT	Vehicle Miles Traveled
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)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		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

SI* (MODERN METRIC) CONVERSION FACTORS				
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
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)

U.S. Department of Transportation
ITS Joint Program Office-HOIT
1200 New Jersey Avenue, SE
Washington, DC 20590

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