Development of an Analysis/Modeling/Simulation (AMS) Framework for V2I and Connected/Automated Vehicle Environment

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Government Task Manager: John Halkias

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16. Abstract

This project developed a conceptual framework for an analysis, modeling, and simulation system for evaluating the impacts of connected and automated vehicle (CAV) technologies on transportation facilities at the strategic and operational levels, providing the basis for future development of CAV-enabled evaluation tools. The objective of this project is twofold: (1) to lay a foundational framework for the development of AMS system that includes connected and automated vehicles, and (2) to engage in small scale CAV AMS development using this framework that encourages future development activities as a step toward the availability of CAV-aware tools for practitioners. The aforementioned framework includes four main components that provide the core for an envisioned CAV AMS system for evaluating the strategic and tactical impacts of CAVs: 1) demand changes, 2) supply changes, 3) operational performance, 4) and network integration. To conduct a proof-of-concept test of a prototype CAV AMS framework, a case study focusing on the operational performance impacts of CAV systems was selected. The case study focuses on the performance impacts of CAV systems in a mixed traffic environment and uses an integrated traffic-telecommunication microsimulation tool that was developed at Northwestern University as a testbed. Using the aforementioned testbed, three sets of scenarios were evaluated. Mixed traffic flow simulations show that connectivity and automated driving can improve traffic flow throughput, stability, and travel time at high market penetrations. AV sensor performance simulations show that distance measurement error has insignificant impact on the performance of traffic flow in the case of low AV market penetration. High distance measurement error (30 percent), however, could lead to a small increase in throughput at high AV market penetrations, though this would depend on the programmed following distances specified for the AVs. Automated truck platooning simulations show that truck platoons formed under the assumed opportunistic platoon formation strategy are of small size (2-4 vehicles) and short duration (mostly less than 50 sec) in the testbed under consideration, as connected trucks activate platooning behavior only if they are following other connected trucks.

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Executive Summary

Connected and automated vehicle (CAV) technology has the potential to radically change mobility in the foreseeable future. The unique features of CAVs, including but not limited to wireless telecommunication and highly automated driving behavior, can affect the performance of current transportation systems, create entirely new modes of transport, affect the various activities and travel decisions of households and individuals, or all three.

To more clearly identify these impacts, this project developed a conceptual framework for an analysis, modeling, and simulation (AMS) system for evaluating the impacts of CAV technologies on transportation facilities at the strategic and operational levels, providing the basis for future development of CAV-enabled evaluation tools. The objective of this project is twofold: (1) to lay a foundational framework for the development of AMS system that includes connected and automated vehicles, and (2) to engage in small scale CAV AMS development using this framework that encourages future development activities, toward a vision where practitioners have CAV-aware tools available.

The comprehensive CAV AMS framework developed through this project includes four main components that provide the core for an envisioned CAV AMS system. Those include:

- **Supply Changes**: to analyze the emergence of new mobility options enabled by CAVs and the changes incurred by the new technology to the infrastructure.
- **Demand Changes**: to evaluate CAV impacts on activity and travel choices.
- **Operational Performance**: to evaluate the impacts of the technology on the performance of transportation systems, such as increased capacity and improved travel time.
- **Network Integration**: to capture the multi-agent interactions at the network level.

The framework addresses three types of gaps identified in existing CAV AMS capabilities: methodological gaps, data-related gaps, and implementation gaps. Methodological gaps were addressed by integrating the missing CAV-related features, such as multitasking and the new robotic behavior, into the different modeling components of the framework. Data-related gaps, which require collecting more data on the actual behavior of CAV systems, were addressed by allowing the models to be updated or replaced once new data or models as they become available. Finally, implementation gaps were addressed by integrating supply, demand, and operational components into an AMS platform.

The selected case study focuses on the operational performance impacts of CAV systems in a mixed traffic environment (i.e., CAVs, human drivers, and trucks) at different market penetration rates for the technology. To do so, the study uses an integrated traffic-telecommunication microsimulation tool that was developed at Northwestern University as a testbed. The microsimulation platform is a special-purpose tool for simulating mixed traffic conditions on freeways in a connected environment. It integrates four distinctive driving behaviors: isolated-manual, connected-manual vehicles (CV), isolated-automated vehicles (AV), and connected and automated vehicle (CAV).

Using the aforementioned testbed, three sets of scenarios were evaluated. Those scenarios analyze the following:

- The performance of mixed traffic flow.
- The impact of AV sensor performance on mixed traffic flow.
- The impact of connected and automated truck platooning on mixed traffic flow.

The mixed traffic flow simulations show that connectivity and automated driving can improve traffic flow throughput, stability, and travel time at high market penetration rates. The AV sensor performance simulations show that distance measurement error has insignificant impact on the performance of traffic flow in the case of low AV market penetration. Connected and automated truck platooning simulations show that active platooning can lead to higher traffic throughput due to trucks driving at shorter distances (i.e., headway) in platoons. Platooning, however, seems to have an insignificant impact on overall travel time. The truck platoons formed under the assumed opportunistic platoon formation strategy are of small size (2-4 vehicles) and short duration (mostly less than 50 sec). Under the opportunistic strategy, connected trucks activate platooning behavior only if they are following other connected trucks. Due to the generally small number of trucks on highways (< 20 percent), forming platoons under this strategy could be difficult, especially over short distances.

Chapter 1. Introduction

Connected and automated vehicle (CAV) technology has the potential to radically change mobility in the foreseeable future. The unique features of CAVs, such as wireless telecommunication and robotic driving behavior, would not only affect the performance of transportation facilities on the tactical level but also impact travel decisions at the household level, the available mobility options, and infrastructure development at the strategic level. Therefore, evaluating the far-reaching impacts of the new technology requires the holistic approach taken by the project team to analyze those impacts on multiple levels.

It is useful first to identify, conceptually, the key phenomena and dimensions that uniquely differentiate CAVs from existing technologies normally captured in available analysis, modeling, and simulation (AMS) tools. This forms the basis for examining the extent to which existing models might capture the demand and performance characteristics of CAVs to develop a comprehensive AMS system (*1*). Some of the key differentiating features include the following:

- CAVs have different performance characteristics and enable different service levels for a given infrastructure.
- System performance is dependent on specific technological features, market penetration rates, as well as degrees of deployment of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications for connectivity.
- On the supply side, entirely new supply and service delivery options may emerge—namely various forms of mobility as a service with shared fleet utilization.
- On the demand side, the likelihood of major activity shifts at the household level increase, the value-of-time changes due to multitasking, and mobility use changes.

Existing CAV AMS capabilities, which were assessed in previous task documents (*2-4*), have been developed primarily to address specific research questions regarding certain impacts of CAV systems rather than providing a toolkit capable of addressing the breadth and depth of issues of concern to agencies engaged in planning and operating transportation systems. To that end, this project aims to lay the foundation for an integrated AMS system capable of evaluating both the strategic and operational impacts of CAV systems on transportation networks. This envisioned system, initially discussed in the Task 3 reports (*5; 6*), will help guide future research and development of CAV AMS capabilities.

Connected Vehicle Systems

Connected vehicle technologies offer the opportunity to create an interconnected network of moving vehicular units and stationary infrastructure units in which individual vehicles can communicate with other vehicles (i.e., V2V communication) and other agents (e.g. a centralized traffic management center through V2I communication) in a collaborative and meaningful manner. The real-time information provided by V2V and V2I improves drivers' situational awareness and enhances the safety and efficiency of operating vehicles. This information also improves the reliability of the traffic system by supporting online monitoring and dynamic management while providing data for both online operations and offline planning applications.

As envisioned by the United States Department of Transportation (USDOT) Connected Vehicles Program, this connected environment serves three main purposes: improving safety, enhancing mobility, and reducing emissions (*7; 8*). Connected vehicle technology is expected to address 81 percent of all imminent crashes by improving drivers' situational awareness (*9*) while reducing or eliminating congestion, decreasing energy consumption, and lessening the negative environmental effects of driving (i.e., by reducing emissions and greenhouse gases).

From a traffic operations perspective, a key focus of connected vehicle systems is to enable coordinated strategies that improve the quality of flow along highways and at intersections, including speed harmonization, cooperative adaptive cruise control, and queue warning (*10*). In general, the more vehicles are connected together, the greater the opportunity for coordinated interventions to improve the quality and reliability of flow. In an urban setting, connected vehicle technology enables more responsive operation of traffic controls, especially traffic signals, and more efficient sharing of right of way by different types of vehicles, including transit vehicles along priority corridors. Connectivity is also envisioned to enable more effective demand management by integrating information to and from travelers into the overall system and improving the overall user experience and multimodal mobility.

The Internet of Things and Smart Cities

Beyond the immediate scope of transportation systems, the notion of an internet of things (IoT) in which machines, objects, people, and vehicles of all types are interconnected is also relevant to the overall mobility picture. At the level of an urban area, the data and systems integration envisioned under an IoT results in so-called "smart cities," where a web of connected sensors of all types combined with shared data platforms enable efficiencies across urban services in different sectors; e.g. education, health care, electric power, water, in addition to mobility services (*11; 12*). In terms of personal urban mobility, the quality, scope, and relevance of real-time information would contribute to reducing waiting times for transit services, enable reservation and payment for parking spots at congested locations, simplify access across a spectrum of urban modes such shared bikes and vehicle fleets, facilitate seamless access to airports and major terminals, and so on. For users, this means greater convenience; for cities and operators, greater efficiencies and better utilization of resources; and for society, more livable and environmentally sustainable cities.

Connected cities with shared data platforms and intelligent processes that leverage the data offer a range of opportunities for end users (city dwellers, travelers), system operators, and managers as well as a plethora of potential services by third parties. The availability of large data streams from various public and private sources, and having the ability to reach consumers almost instantly through mobile connected devices, creates many new opportunities for entrepreneurial third parties to improve existing services or offer entirely new categories of services and experiences, including in the realm of both person and goods mobility. From a research perspective, a variety of new problem classes arise in connection with the availability of these data streams, for both online system operation and service delivery as well as offline characterization of the demand for mobility and related services. In summary, connectivity and the very existence of the IoT increase opportunities for users, for the overall system, and for third parties.

One of the substantial hurdles for achieving the kind of integration envisioned under smarter urban systems, as it is for connected vehicle systems, is the sheer requirement for intra- and inter-agency coordination and process redesign that may be more difficult to accomplish in certain cities than in others. For connected traffic systems, the mission-critical nature of both the telecommunication and the control systems required to maintain safe operation calls for levels of sophisticated coordination that are not typical in existing operations. Hence, the vision of the connected vehicles program, like the emerging vision for smart connected cities, may have gotten way ahead of any implementation. The difficulty in achieving the public-private commitment to deploy has, in part, motivated the emergence of entirely automated vehicles, or self-driving cars, discussed next.

Automated Vehicles

The popular media has been replete with images of automated, or driverless, cars over the past few years, especially the "Google car"—the well-publicized entry into the vehicular realm by the technology giant. The vision is certainly not new, and one can find examples of images depicting cars driving themselves while the occupants engage in work or recreational activities as far back as the 1930s (*13; 14*). However, advances in computing, robotics, and artificial intelligence have enabled near road-worthy vehicles, prompting serious efforts in the regulatory, legal, and insurance spheres pertaining to the entry of such vehicles into everyday utilization.

The primary classification of driving automation systems is based on the division of roles between the human operator and the automation system. SAE (*15*) has defined five such levels, in addition to specifying a "zero automation" level in which the human driver drives normally, but may be assisted in maintaining safety by warning systems or control systems that intervene for short periods of time with braking or steering actions (such as yaw stability systems or anti-lock brakes). Those levels are:

- Level 1 – Driver Assistance.
- Level 2 – Partial Driving Automation.
- Level 3 – Conditional Driving Automation.
- Level 4 – High Driving Automation.
- Level 5 – Full Driving Automation.

Automated vehicle capabilities are often discussed in conjunction with connected vehicle systems, although the two are, in effect, distinct. The former is envisioned as the ability to drive with no external assistance, possible through extensive sensing and massive intelligence fully residing *within* the vehicle. All these functions could be enhanced through connectivity; e.g., when neighboring vehicles and/or the infrastructure convey messages to other vehicles about respective locations, road features, or control displays. Additional coordinated strategies could thus be enabled to further enhance safety and flow quality. However, in that case, more of the intelligence resides in the infrastructure, or the vehicle-infrastructure system, rather than residing exclusively within individual vehicles. These factors have important implications for deployment, coordination, vulnerability, and resilience of the associated system. Most notably, connected vehicle systems require a much greater degree of coordination amongst auto manufacturers and traffic management authorities (generally public sector), whereas Level 4/5 automated (also called autonomous) vehicles are envisioned as being fully self-sufficient (given the existing physical infrastructure).

Several studies of both automated and connected vehicles were conducted in the 1990's (*16-21*), and more recently in the past 5 years (*22-25*), to investigate the flow properties of vehicular traffic streams with varying fractions of automated and/or connected vehicles. While these properties will be determined by the specific technologies and how they are implemented (e.g., the specific logic by which a driverless vehicle would follow other vehicles, change lanes, and so on), the sensors used, the pattern recognition algorithms, and the interaction protocols for vehicles with different levels and types of technologies, investigations to date suggest meaningful improvement in most flow performance indicators. Nonetheless, these studies have been limited to simulation-based analyses with some field information from small-scale technology demonstrations. Hence considerable additional effort is required to fully ascertain the flow impacts of these technologies for specific deployment scenarios.

Scope of Project

To evaluate the potential impacts of CAV technologies, transportation agencies must be equipped with the necessary tools to predict the impacts of those technologies in order to support decision making at the planning and operational levels. This project aims to build a conceptual framework for an AMS system for evaluating the impacts of CAV technologies on transportation facilities at the strategic and operational levels, providing the basis for future development of CAV-enabled evaluation tools.

Objective

The objectives of this project are twofold: (1) to lay a foundational framework for the development of an AMS system that includes connected and automated vehicles and (2) to engage in small-scale CAV AMS development using the framework to encourage future development activities and advance a vision in which practitioners have CAV-aware tools available.

Chapter 2. A Comprehensive Methodological Framework for Connected and Automated Vehicle Analysis, Modeling, and Simulation

The implications of connected and automated vehicle (CAV) technology are far reaching at both the strategic and operational levels, yet those impacts are interdependent (*26*). On the strategic level, the technology will potentially affect the supply of mobility services, demand patterns, and travel behavior. On the operational/tactical level, the technology can potentially improve traffic flow performance on transportation facilities and networks.

CAV technology is expected to help introduce entirely new modes of mobility (*27; 28*)—in the form of shared-automated-vehicle (SAV) fleets, for example—in addition to improving multiple aspects of current mobility options. Such improvements include highly automating certain driving tasks (or all of them) from origin to destination and supporting travel-related decisions by providing real-time information through wireless telecommunications.

The availability of new mobility forms in addition to the improvements to current transportation systems through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) connectivity can affect the activity patterns (*29-33*) and the mobility choices of travelers (*34; 35*). Those changes can involve household-level decisions, such as owning a car, or individual decisions, such as departure times and route choices (*36*).

Changes to both supply and demand, in addition to the improvements to traffic flow brought by connectivity and automation, ultimately affect the operational performance of transportation systems. The potential improvements include, for example, increased throughput (*20; 37-42*) and improved safety through incorporating real-time information (*43-46*) on prevailing traffic conditions and the addition of a safer automated driving behavior (*17; 22; 47-50*).

To that end, this section introduces a comprehensive framework for evaluating the strategic and operational impacts of CAV technology on transportation facilities, illustrated in Figure 1. The framework includes four main components:

1. **Supply Changes** to analyze the emergence of new mobility options enabled by CAVs and the changes incurred by the new technology to the infrastructure.
2. **Demand Changes** to evaluate CAV impacts on activity and travel choices.
3. **Operational Performance** to evaluate the impacts of the technology on the performance of transportation systems, such as increased capacity and improved travel time.
4. **Network Integration** to capture the multi-agent interactions at the network level.

The main components of the framework are interrelated and, therefore, should be integrated into a comprehensive analysis, modeling, and simulation (AMS) system for an improved evaluation of CAV impacts. The remainder of this chapter discusses the four main components and their integration within a CAV AMS system

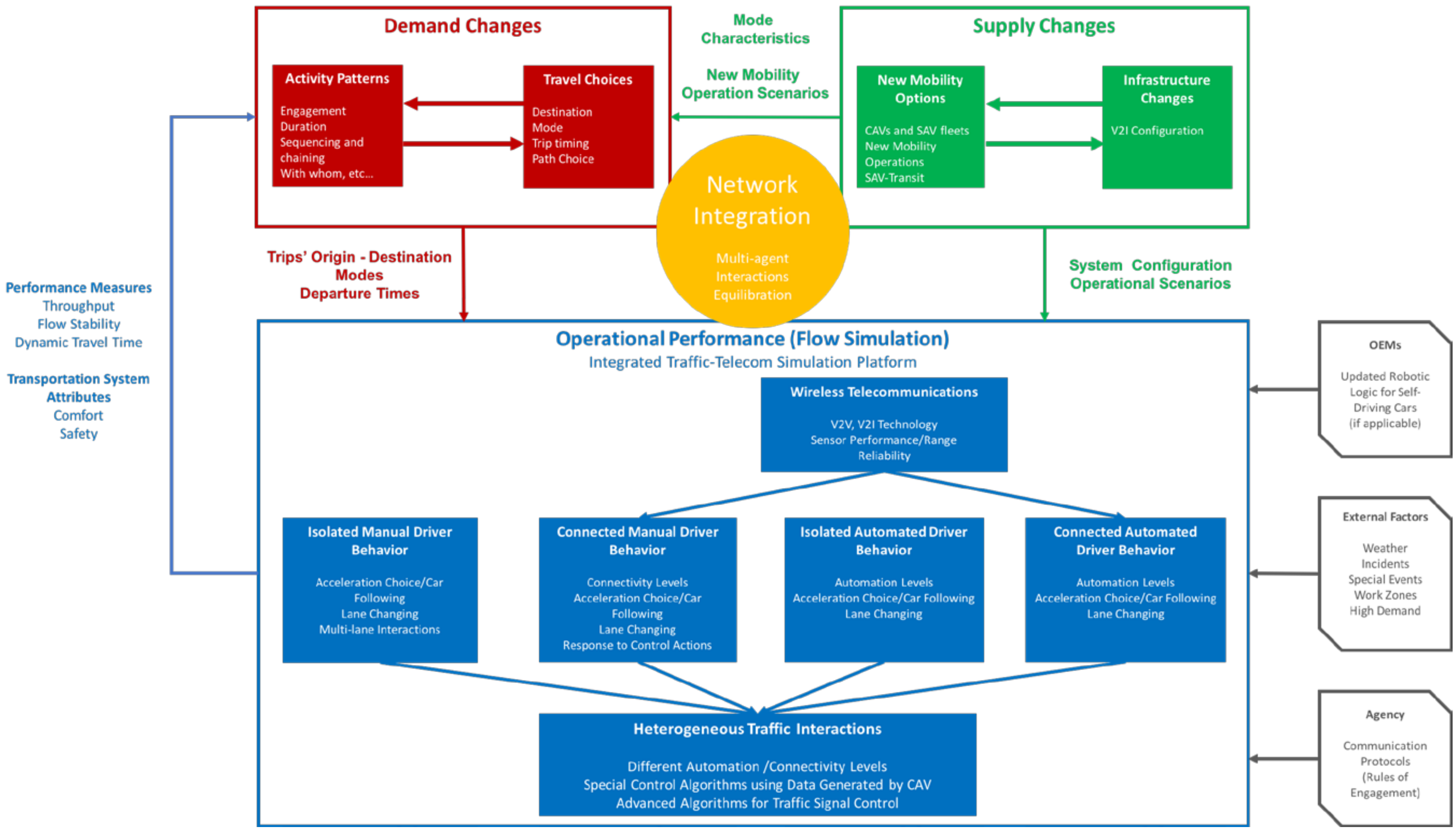

Figure 1. A methodological framework for evaluating the strategic and operational impacts of connected and automated vehicle technology.

Demand Changes

The new forms of mobility (*27; 28*) enabled by CAV technology and their expected improvements to the performance of transportation systems could lead to fundamental changes to the transport-related decisions. Those changes could affect 1) the activity patterns (*29-33*) and 2) the mobility choices of travelers (*34; 35*) at multiple levels, as illustrated in Figure 2.

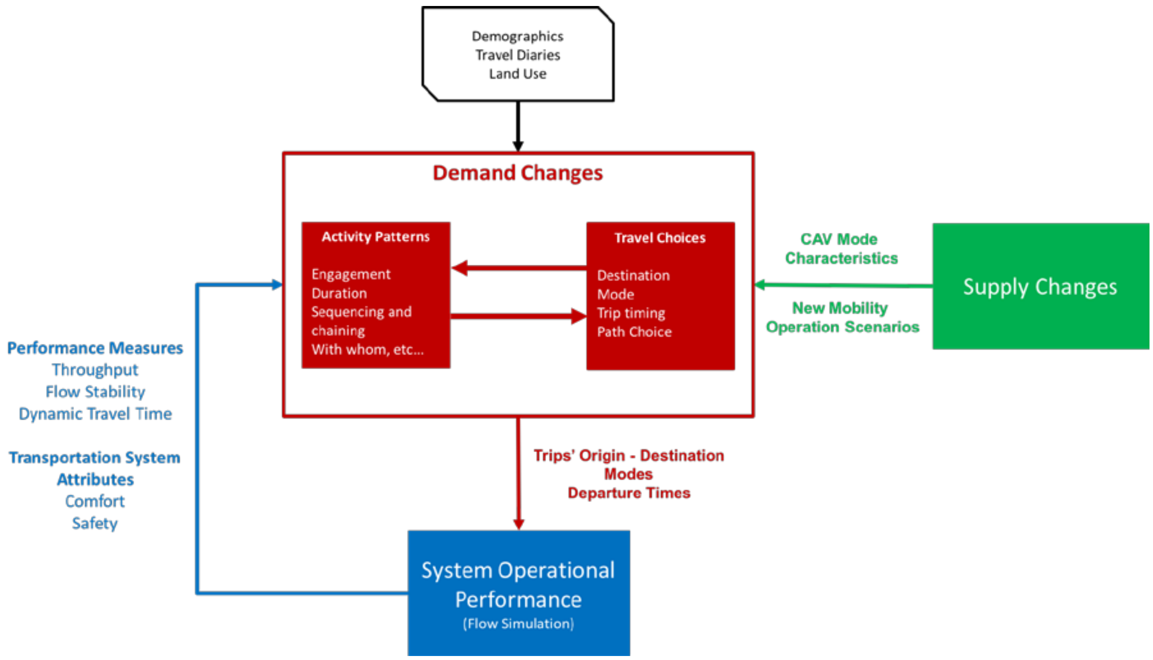

Figure 2. The demand changes component of the general connected and automated vehicle analysis, modeling, and simulation framework.

Activity Patterns

On the higher level, the potentially improved features of the new mobility options can impact the activity patterns of households and businesses. One key feature of highly automated vehicles is enabling multitasking during vehicle operation, which would make time that is usually lost in driving a productive one. For example, travelers can do their work while being driven to their office. Thus, the value of individuals' travel time might change as travelers may not mind spending more time moving in a vehicle. In addition, having a robotic "chauffeur" to assist in daily chores can reprioritize activities in the household. For instance, highly automated vehicles could pick up kids from school or groceries from the store.

Other characteristics of the new technology, such as potentially greater safety and lower cost of SAVs, could affect other high-level decisions, such as owning a vehicle (*51-55*). Households may require fewer owned vehicles since those vehicles can drive themselves and efficiently serve multiple members of those households. The new shared-automated service may eliminate the need to own a vehicle altogether if the service proves to be reliable and affordable. Vehicle ownership by businesses can also be affected by automated vehicle technology. With safer, more efficient, and more sustainable distribution, businesses may require fewer vehicles to deliver goods to their clients. They might also share automated vehicles for delivery to achieve higher utilization and lower costs.

Travel Choices

On the tactical level, some of the new features of automated vehicles (AVs)—mainly the ability for passengers to multitask during the trip—can affect individual trip decisions (*36*) as to mode choice, route choice, and departure time, among others. The usual assumption is that human drivers choose travel routes that minimize their travel time according to the best information they have available. However, travel times are dynamic, depending on prevailing traffic conditions, and may not be readily available to non-connected drivers at the time they choose their routes. Connectivity can affect route choice in several ways. One way would be for connected vehicles to act as probes to traffic conditions and share that information with other connected vehicles. This would enable more accurate estimates of travel times and shortest routes. Another way would be for automated or connected vehicles to reroute themselves while moving towards a destination based on developing traffic conditions, which can lower costs and travel time.

As for mode choice, connectivity allows for new mobility tools and better intermodal integration. Travelers would be able to use multiple modes conveniently; for example, using public transit and a shared-automated-vehicle (SAV) service. Users may also shift to entirely different modes, like solely using SAVs instead of driving personal vehicles or taking transit.

Departure times can also be affected by CAV technologies. With less variable travel times, travelers may not need to leave much earlier than they should to account for unforeseen delays. Additionally, travelers living in the same household can share an automated vehicle and coordinate their departure times. For example, parents can send their children to school in the highly automated car while getting ready to leave for work before the car comes back.

Integrating the Demand Changes Component within a Connected and Automated Vehicle Analysis, Modeling, and Simulation System

The objective of the Demand Change component in the general framework is to predict activity patterns (i.e., trips, origins and destinations (ODs), and routes) and travel choices (i.e., modes, departure times) influenced by CAV technology and new mobility options, as defined in the scenarios produced from the Demand Changes component (see Figure 2). The demand changes component, which includes trip duration, mode choice, and timing, will be predicted using robust demand models within which the multitasking feature is explicitly integrated.

Changes in demand, such as longer trip durations, a greater number of trips, or different paths chosen for the trip, influence the demand flows used in performance models to evaluate the new system's attributes in the presence of CAV technology at the operational level. The new attributes (e.g., travel time, comfort, and reliability) produced by performance models (e.g., dynamic traffic assignment tools or microsimulation) will update mode characteristics in demand models and reproduce demand flows. The loop of updating demand flows and system attributes, which is exchanged between demand and performance models, stops when a convergence criterion or criteria is met. Examples of such criterion include activity schedule consistency and improvement in travel time.

Supply Changes

The major supply changes expected from the deployment of CAV systems are 1) new mobility options and services and 2) infrastructure modifications to enable wireless telecommunications. The new mobility services will mainly be in the form of a shared automated vehicles (SAV) and hybrid systems enabled by SAVs (*53; 56; 57*). New mobility services also includes automated truck systems, potentially resulting in disruptive impacts to the trucking industry (*58*). The aforementioned changes are captured in the supply component of the CAV AMS framework as illustrated in Figure 3.

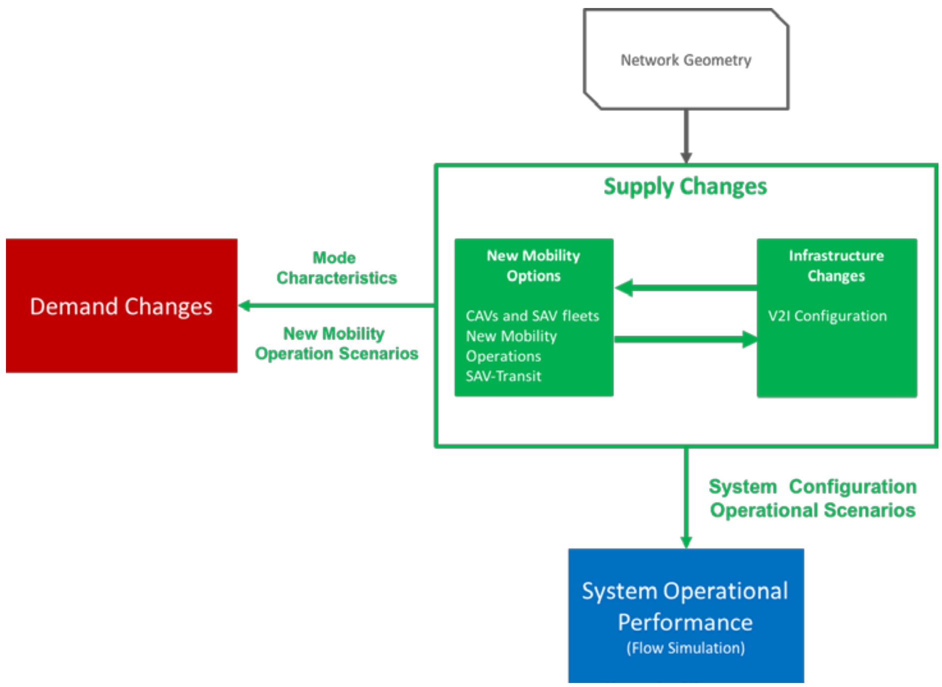

Figure 3. The supply changes component of the general connected and automated vehicle analysis, modeling, and simulation framework.

New Mobility Options

The rapid development in wireless telecommunication technologies and the high adoption rate of those technologies have enabled radically new forms of mobility and opportunities for multi-mode integrations that were not possible or thought of less than 20 years ago. Most AMS tools, for example, failed to predict current ride-hailing services, such as Uber and Lyft, which were only enabled by advancements in positioning, telecommunication, and handheld computing technologies.

The recent advancements in the areas of artificial intelligence, robotics, CAV systems, and the Internet of Things (IoT) will probably cause even more radical changes to the forms of mobility that travelers are used to. Aside from the extremely futuristic modes such as flying cars or the Hyperloop,[1] the most anticipated mode enabled by the aforementioned technologies is SAV fleets.

SAV fleets or their hybrid systems will play a key role in expanding mobility-as-a-service (Maas) and creating integrated forms of mobility in the future. For example, a new mode can be an integrated transit-SAV system where the latter serves as a first/last mile connection. While shared vehicle fleets are not an entirely new form of mobility, transport network companies (TNC) such as Uber and Lyft already offer this service. SAV have two main differentiating features: (1) the automated driving behavior of vehicles is different from the human driving behavior, and will likely impact the overall performance of the system, and (2) the mobility service owner would have full control over the system, unlike services using human drivers, and can optimize the service to serve different objectives, such as minimizing costs or maximizing quality. These two features have the potential to increase the SAV market share and competitive advantage against other modes.

Furthermore, connectivity can enable better integration of multiple modes for improved mobility. One specific case is public-private partnerships to solve the first/last mile problem of access to transit systems. Through a connected platform, for example, TNCs can integrate their services with transit systems to provide better accessibility and more convenient transfers. Consequently, improving transit services through such partnerships can increase ridership and potentially reduce the need to use private cars.

In addition to personal mobility, the logistics industry could be one of the early adopters of automated vehicle technology, as it promises improved safety, sustainability, and efficiency of goods movement (*58*). Using automated trucks improves safety by reducing human errors. As for sustainability, automated truck technology can lower emissions by potentially improving fuel consumption. Finally, in the long term, highly automated trucks can increase operational efficiency because machines, unlike drivers, do not need breaks during or between trips.

Infrastructure Changes

The second major supply impact as a result of CAV technology deployment is the potential change to the infrastructure to enable wireless telecommunications. This unique feature of CAV systems is often missing in existing CAV AMS capabilities. Reliable wireless telecommunication is both essential for the operation of CAV technologies and can affect the driving behavior of CVs. Most AMS tools, especially SAV fleet models, assume that all vehicles are connected and the central dispatcher has full information regarding the location of all vehicles, requests, origins, and destinations. This may not be the actual case in practice.

Furthermore, V2I technology, depending on the technology type, is likely to be deployed in strategic locations due to its high costs. This will impact the operations of SAV fleets that rely on a central dispatcher to assign vehicles. Furthermore, wireless telecommunications, even the most advanced technologies to date, may not be reliable at all times. The system may suffer from outages, disconnections, or poor signals,

[1] A hyperloop is a theoretical transportation system that would propel bullet-like pods over long distances through steel tubes using magnetic levitation and vacuum pumps to abate friction and air resistance, allowing the bus-sized pods to travel at speeds approaching Mach 1.

especially at severe weather conditions. Similar reliability issues involve the positioning of vehicles such as lost GPS signals inside tunnels.

For the abovementioned reasons, having an abstract representation of wireless telecommunications in CAV AMS systems is important for providing a realistic representation of new mobility options and evaluating the impacts of telecommunications reliability on driving behavior. In this methodological framework, wireless telecommunication technologies (V2I, V2V, and vehicle-to-everything (V2X)) are integrated within the network representation. The representation would include communication ranges that affect the information flow between connected agents (travelers, vehicles, and infrastructure).

Integrating the Supply Changes Component within a Connected and Automated Vehicle Analysis, Modeling, and Simulation System

Three main aspects of mobility supply changes would need to be addressed in an AMS system intended to examine CAV impacts: (1) predicting the emergence of specific services (and their characteristics), along with shifts in the transit system, (2) generating optimal plans to operate these fleets and services, and (*3*) evaluating the impact of these services on the transportation system.

The first of the above aspects is beyond the capability of any tool and is one of the main gaps in existing CAV AMS capabilities. The second aspect is what most studies have focused on (*59*) by building special-purpose simulation tools (*54; 56; 60; 61*) to answer questions related to managing SAV fleets, such as the number of vehicles required, travel time, costs, etc. The third aspect is achieved by integrating the first two aspects with the demand component in an AMS system to evaluate the impacts at a network level.

As developing a full capability to predict emerging mobility option can be a very complicated process, the supply changes component in the CAV AMS system should allow the analyst to define multiple operational scenarios for new modes and the wireless telecommunication technologies in place, whether it's V2I, V2V, or V2X communications. Those scenarios will be based on current and predicted market trends; technology development; regulations; and, ultimately, expert judgment.

The assumptions about supply changes are integral to evaluating demand changes and operational performance. As illustrated in the framework in Figure 1, the defined scenarios will determine the availability of new modes, their characteristics, and the type of new telecommunication technology in place. Those assumptions will define the system configuration, regardless of its scale (network, corridor, or a facility), based on which demand changes and operational performance will be evaluated. As a result, defining those scenarios will reduce the uncertainty related to the impacts of the new technology.

Operational Performance

The most direct impact of CAVs on network performance will result from the operational performance characteristics of the vehicles in the traffic stream, and the control algorithms enabled by and deployed with varying degrees of V2V and V2I connectivity (*18*). CAV systems are expected to improve different performance aspects (*62*) of transportation systems, including safety (*9; 63*), mobility (*1; 7*), and sustainability (*64*). The technology promises to reduce accidents that are caused by human error, improve road capacities by driving safely at higher densities (*65*), and improve traffic control whether on freeways (*17; 37; 38; 41; 42; 49; 66*) or intersections using advanced wireless telecommunication technologies (*19; 67-78*). While greatly dependent on decisions made in the commercial marketplace, public agencies, and regulatory bodies, understanding and modeling these impacts under a given set of assumptions about technological features, deployment scenarios, and control measures is an essential AMS requirement that lies mostly in the realm of traffic physics.

To fully capture the traffic impacts of CAV systems, AMS models should capture the heterogeneous interactions between different driving behaviors. First, there will be isolated manual drivers who have relatively higher reaction times and risks of driving errors (e.g., new drivers, older drivers). Second, there will be connected and well-informed drivers who are more aware of their surroundings and presumably with better reactive behavior. Finally, there will be the new driving behavior with the introduction of highly automated vehicles, which can also be connected through wireless telecommunications. This behavior would heavily depend on the equipped sensors and the control algorithms installed by car manufacturers in addition to the supplementary information that can be received through connectivity.

The operational performance component of the envisioned CAV AMS system is an integrated traffic-telecommunication simulation platform that can simulate mixed traffic conditions under different operational assumptions and scenarios. The performance component, illustrated in Figure 4, includes four types of driving behaviors: (1) isolated-manual, (2) connected-manual, (3) isolated-automated, and (4) connected-automated. It also includes a wireless telecommunication component that specifies the performance of the communication systems relevant to transportation system performance. Finally, the tool includes a component to simulate heterogeneous interactions among the different driving behaviors (depending on the assumed connectivity/automation levels) and the implemented control algorithms.

As inputs to the integrated simulation platform, the framework includes demand patterns and the system configuration, which are outputs of the strategic-level analysis as discussed in the general framework (Figure 1). In addition, external factors (e.g., weather), logic for controlling automated vehicles, and the agency's communication protocols are considered in the integrated simulation platform. Finally, the simulation tool outputs both pre-defined and user-defined performance measures to evaluate the impacts of CAV technology on the system's performance. The remainder of this section discusses the major components of the performance simulation tool in further detail.

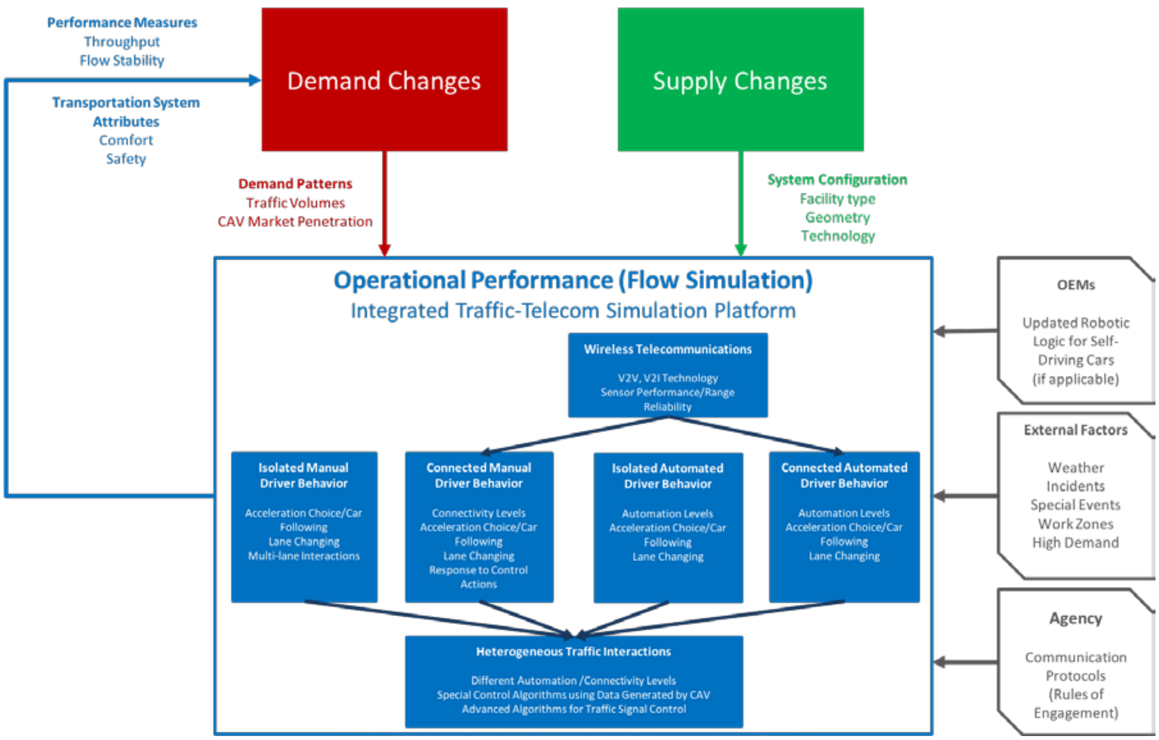

Figure 4. The operational performance component of the general connected and automated vehicle analysis, modeling, and simulation framework.

Wireless Telecommunication and Sensors

The CAV AMS modeling system needs to provide for an appropriate level of representation for the effects that the enabling technologies for CAVs will have on the behaviors of the automated vehicles and their interactions with the transportation management functions. The most important of these technologies are the telecommunications and environment-perceiving (sensing) technologies, but these are also closely coupled with positioning technologies. These technologies typically function on time scales much shorter than the time scales associated with vehicle motions, but that does not mean that they need to be modeled at those very short time scales (which would have adverse consequences for computational efficiency). The phenomena that influence their performance are often very different from the phenomena that are represented in transportation network models (for example, ambient lighting conditions and atmospheric conditions that affect radio wave propagation and visibility, including disturbances such as electrical storms and sunspots). These considerations point toward the need for simplified models focused on the aspects of sensor and communication system performance that directly influence vehicle performance.

Connected Manual Driver Behavior

Connectivity extends drivers' perception of their surrounding environment beyond the visual scanning capabilities of isolated drivers, theoretically leading to more responsive driving behavior (*25*). Depending on the type of communication, V2V and V2I provide different information to drivers and affect their behavior accordingly. V2V provides information on vehicle movement and location, such as speed and acceleration of downstream vehicles, which increases drivers' awareness of downstream traffic conditions and improves their responsiveness (lower reaction time). V2I, on the other hand, provides information on road conditions, weather, and TMC decisions (e.g., express lanes), which influence the drivers' strategic decisions about route choice and departure time.

Because of the above-discussed influences of connectivity on driving behavior, the proposed Performance Simulation Tool explicitly distinguishes between the two manual driving behaviors (connected vs. isolated) and uses different acceleration/lane changing formulations to model them.

Automated Driving Behavior

A great diversity of driving automation systems will have to be represented by the CAV performance simulation tools since the systems under development and consideration vary widely from each other. The main dimensions that can be used to characterize driving automation systems include:

1. Society of Automotive Engineers (SAE) levels of automation – a system that defines which roles are performed by the automation system and which roles are performed by humans.
2. Degree of coordination or cooperation – is the system autonomous or does it rely on V2V, I2V, or more general V2X information?
3. Operational design domain (ODD) – the specific conditions under which the driving automation system is designed to function, including roadway type, traffic conditions and speed, geographic locations (boundaries), weather and lighting conditions, condition of pavement markings and signage, availability of other necessary supporting infrastructure features, etc.

Different Automation Levels, Different Connectivity Levels

The levels of automation are defined precisely in the SAE J3016 Recommended Practice document (*15*). This is an important reference that all modelers and designers of automated systems should study. The simplified version of the SAE J3016 classification criteria can be distilled into the answers to the following questions:

1. Does the driving automation system perform <u>either</u> the longitudinal <u>or</u> the lateral vehicle motion control task in a sustained fashion, but not both? If yes, it is a Level 1 system. Many of these are already available to the public (such as adaptive cruise control or lane tracking systems).
2. Does the driving automation system perform <u>both</u> the longitudinal and lateral vehicle motion control tasks in a sustained fashion simultaneously? If yes, it is at least a Level 2 system. Some Level 2 systems are already available on premium vehicles and many more are under development, but at this level they still require the driver to continuously monitor the system performance and the driving environment for potential hazards.
3. Does the driving automation system <u>also</u> perform object and event detection and response? If yes, it is at least a Level 3 system. At this level, drivers can temporarily divert their attention away from the dynamic driving task to perform other tasks (such as reading or web surfing), but they need to be available to resume driving when the system requests help. None of these systems have been brought to the market yet, and there is controversy within the industry about whether it is possible to make such a system safe.
4. Does the driving automation system <u>also</u> perform the dynamic driving task fallback function, ensuring recovery from all internal faults or external hazards without requiring driver intervention?

If yes, it is at least a Level 4 system. Some of these systems may not require any driver if their operation is confined to locations where the Level 4 operations can be guaranteed to function all the time (such as airport people movers in physically protected rights of way). A wide range of Level 4 systems are under development, but the critical aspect that needs to be defined clearly is the unique operational design domain for each system.

5. Is the driving automation system limited to operations within a specific operational design domain (ODD)? If it is not limited by an ODD, but is capable of driving safely under the full range of conditions in which humans can drive safely, it is a Level 5 system. That is a very long-range prospect, not something that needs to be planned for within the foreseeable future.

The level of automation of any specific driving automation system determines which aspects of its behavior need to be modeled as automated and which aspects need to be modeled as normal human driving behavior (using baseline driver car-following or lane-changing models).

Heterogeneous Traffic Interactions

Different Automation Levels, Different Connectivity Levels

The introduction of CAV on the road will lead to different types of drivers sharing the same transportation facility. To evaluate the flow impact of the traffic interactions among the heterogeneous driving styles, and since the actual CAV market share is a variable that can be chosen to have many different values, the performance simulation component should be able to simulate multiple scenarios at different CAV market penetrations. This would help planners and policy makers prepare for the impacts of CAV in the short and long-term as the market penetration of CAV is expected to start small and grow as the technology matures.

Special Control Algorithms

In addition to evaluating mixed traffic, the Performance Simulation Tool can be used to evaluate special control algorithms designed for the CAV environment. For example, the simulation tool can be used to evaluate a special speed harmonization algorithm that utilizes more accurate traffic volumes available through V2V communications and to send speed limit information directly to connected drivers instead of using fixed signs. Another example of a special algorithm is a queue warning system that uses vehicle locations through V2V communications to accurately detect queues and directly warn drivers upstream of queues instead of through fixed message signs.

Performance Measures (Metrics)

This subsection identifies the performance measures to be used in the Performance Simulation Tool to evaluate the impacts of CAV-technologies on operational performance. Six main categories of measures, summarized in table 1 are identified below (*26*):

- Safety.
- Throughput.
- Flow Stability.
- Flow Break-down and Reliability.
- Sustainability.
- User-defined Performance Measures.

Safety

Safety is an essential factor in evaluating the impacts of CAV-technologies. As the majority of crashes are due to human error, automated vehicles have the potential to significantly decrease the number of crashes, specifically at high market penetration levels. Because crashes are rare events that are not predictable by operational models, this is the most difficult measure of effectiveness to assess with any fidelity. However, such assessments can be made through proxy measures such as the number of instances where an emergency deceleration is required or the time-to-collision (i.e., below some threshold).

Throughput

As discussed in previous sections, CAV technologies are expected to increase the flow throughput of transportation facilities by increasing flow densities. However, such impacts are dependent on the market penetration of those technologies. Throughput can be quantified by measuring the number of vehicles passing through a specific point per hour.

Stability

Flow stability refers to the traffic stream's ability to recover its steady-state properties (density-speed) after incurring a perturbation. The study team found several stability indices in the literature that can be used in the Performance Simulation Tool.

Flow Break-down and Reliability

Flow-breakdown is a traffic phenomenon in which throughput drops due to a perturbation (e.g., accident or sudden braking). CAVs are expected to improve traffic flow reliability by providing a smoother, safer, and more responsive vehicle operation, but their interactions with manually driven vehicles are more complicated. The Performance Simulation Tool can use multiple measures to quantify CAV impact on flow breakdown and reliability such as (1) occurrence of shockwaves, and (2) severity of shockwaves formed.

Sustainability

The environmental impacts of CAV are uncertain. On one hand, smoother operations associated with CAV can lead to lower GHG emissions and energy consumption. On the other hand, the CAV impacts on travel demand are uncertain and could result in higher overall travel volume, which would increase emissions and energy consumption. The trade-offs between greater flow efficiency and greater demand requires further research.

Calculating emissions and energy consumption is usually an offline process that uses data previously obtained by simulation (as in the case of the CAV Performance Simulation Tool) or observed data (*79*). Several methods are available in the literature for that purpose at different data aggregation levels. For the proposed Performance Simulation Tool, emissions and fuel consumption can be calculated using the speed profiles of vehicles (trajectories) at a high temporal resolution, which is obtained by the simulation platform. The proposed performance measures include carbon dioxide (CO_2), nitrous oxides (NO_x), particulate matter (PM) emissions, and the amount of energy consumed.

User-defined Performance Measures

In addition to the performance measures pre-defined within the Performance Simulation Tool, users should be able to define and calculate their own measures using raw performance data generated by the Performance Simulation Tool. For example, users should have access to vehicle trajectory data, traffic control data, and communication messages to create their own visualizations or performance graphs.

Table 1. Summary of proposed performance measures in the connected and automated vehicles performance simulation tool.

Category	Impact	Performance Measure
Safety	Improve safety outcome	Surrogate Safety Assessment, but will require new development work to define suitable measures of effectiveness (MOEs) for connected and automated vehicles (CAV).
Throughput	Traffic flow volumes	Number of vehicles per hour per lane
	Smoothness of traffic flow	Variability of speeds within traffic stream
	Corridor/ Intersection Capacity Utilization	Green Occupancy Ratio Intersection Degree of Saturation
	Intersection Control Performance	Control Delay
Flow Stability	Local stability	Local flow stability index
	String stability	Mixed-flow string stability index
Flow Breakdown and Reliability	Occurrence of traffic shockwaves	Number of significant shockwaves formed Speed variance
	Severity of shockwaves	Propagation speed of formed shockwaves relative to wave front
		Duration of shockwave-induced queues
Sustainability	Impact on GHG emissions	Level of carbon dioxide, nitrous oxides, and particulate matter equivalent emissions
	Energy consumption	Amount of energy consumed

Source: FHWA 2018

Network Integration

Evaluating the network-wide impacts of CAV systems requires capturing the interactions of different agents in a network context. Those agents include CAVs, travelers, mobility service providers, transit and network managers, freight shippers, and carriers. To capture these interactions, model platforms that integrate various components relevant to the questions being asked are required. Platforms in this context are primarily conceptual analytical constructs that are embedded in a software tool. They typically entail a collection of models representing interacting agents or processes. In this case, the CAV AMS system would be a platform that integrates a collection of supply, demand, and performance models to represent the behavior of CAV systems and their impacts on transportation systems, as illustrated in Figure 5. Platforms also typically offer a foundation upon which additional capabilities may be built, albeit with varying degrees of difficulty and effort.

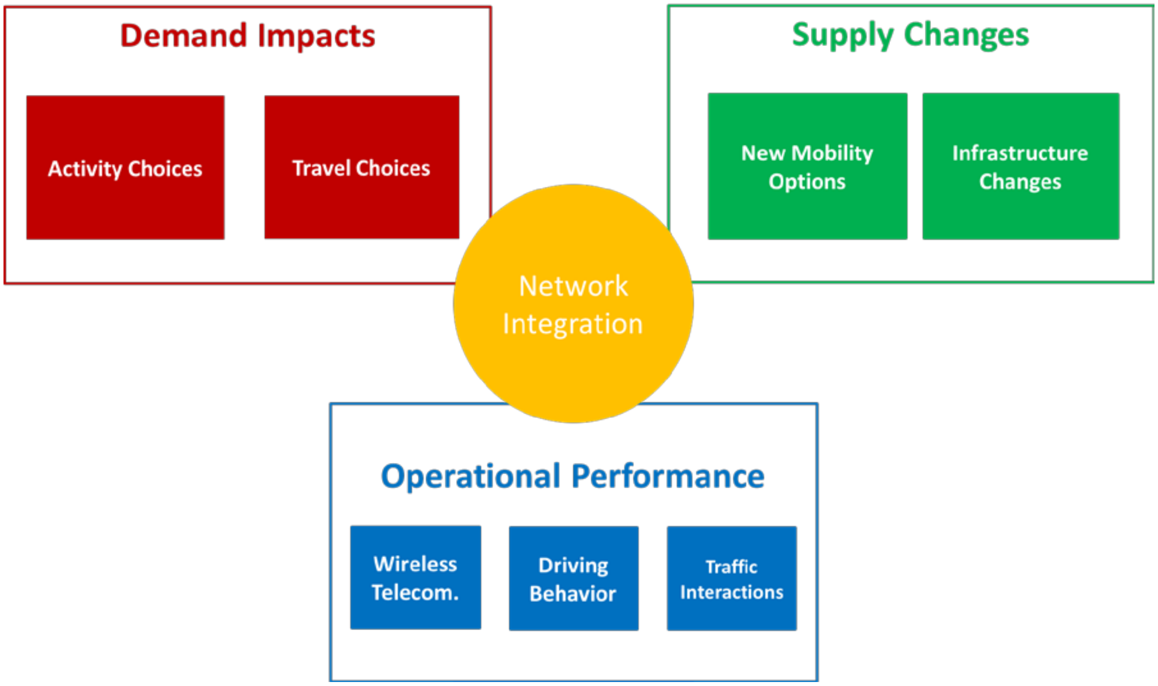

Figure 5. The network integration component of the general connected and automated vehicle analysis, modeling, and simulation framework.

Chapter 3. Connected and Automated Vehicle Analysis, Modeling, and Simulation System Requirements

This chapter identifies the analysis, modeling, and simulation (AMS) system requirements for evaluating the strategic as well as the operational impacts of connected and automated vehicle (CAV) technology on transportation facilities (Figure 6). Those requirements are based on the stakeholder's need identified in the Concept of Operation and the survey conducted by stakeholders on modeling CAV technology. Four types of requirements are identified:

- Functional requirements: related to the functions that should be included in each component of the AMS system.
- Performance requirements: related to the performance of each component as well as the whole system.
- Data requirements: related to data storage/generation of the system.
- Integration requirements: related to the integration of the main components of the system.

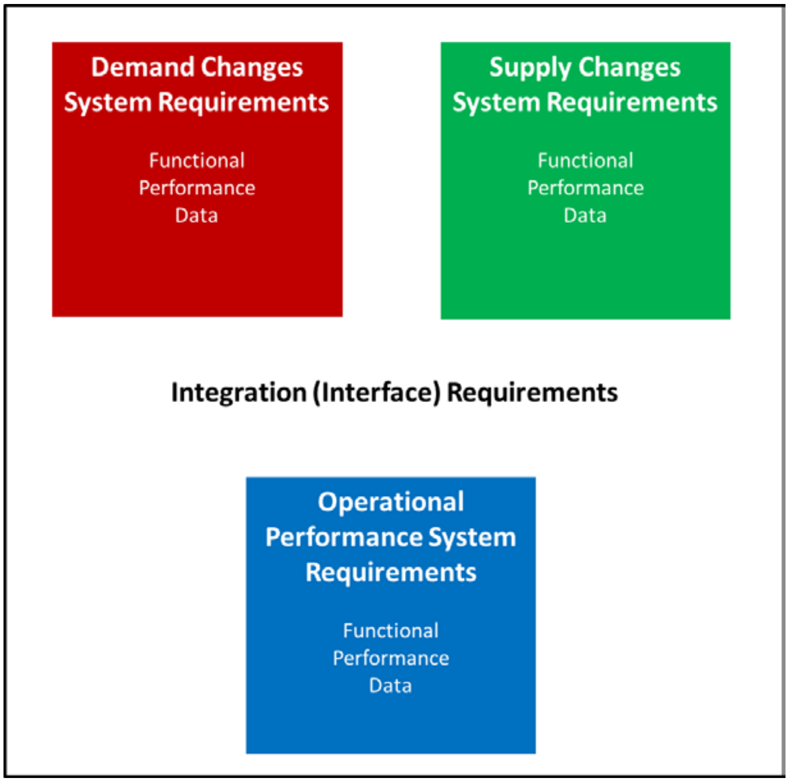

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Figure 6. System requirements of the analysis, modeling, and simulation system.

System Requirements for Evaluating the Strategic Impacts of Connected and Automated Vehicle Systems

This section summarizes the high-level system requirements for evaluating the **strategic** impacts of CAV technology. Below is a description of the table's columns:

- **Framework Component**: groups the requirements according to the two main components in the strategic framework for evaluating CAV impacts: 1) Supply Changes and 2) Demand Changes.
- **Req. ID**: the system requirement identification number. (Note: SC refers to Supply Changes while DC refers to Demand Changes.)
- **Req. Type**: As defined in Figure 6—Functional (F); Performance (P); Data (D); Integration (I).
- **System Requirement**: description of the system requirement.
- **Notes**: additional notes related to the system requirement.
- **Priority**: related to the implementation of the requirement. Four priorities were identified:

1. A: Absolute (Essential).
2. H: High.
3. M: Medium.
4. L: Low.

Table 2. System requirements for evaluating the strategic impacts of connected and automated systems.

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Supply Changes	SC-1	F	The system shall predict/assume the characteristics of new mobility options enabled by CAV systems	Examples of emerging modes include Shared-Automated-Vehicle fleets and new multimodal options. Mode characteristics examples include cost, travel time, and comfort	A
	SC-2	F	The system shall update the characteristics of new mobility options as new information becomes available	Example: actual data when emerging modes are operational	A
	SC-3	F	The system shall predict the area-availability of emerging mobility options and CAV technologies	Examples: city center, urban, sub-urban, rural or specific parts of networks	H
	SC-4	F	The system shall define opportunities for new multimodal integrations enabled by CAV systems	Example: Transit and Shared-Automated-Vehicle fleets in city center	M
	SC-5	F	The system shall determine the type of wireless telecommunication technology to be used (V2V/V2I/V2X) and its location on the network	Example: not all intersections or links on the network will have V2I communications, at least at the beginning	A
	SC-6	F	The system shall define/predict protocols for V2I/V2V/V2X communications	Examples: communication range, frequency of information broadcasting, and amount/type of information stored/used for active control algorithms	A

Table 2. System requirements for evaluating the strategic impacts of connected and automated systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Supply Changes (cont'd)	SC-7	P	The system shall produce a network/transportation system configuration to be evaluated by the other two components of the system: Demand Changes and Operational Performance.	The system configuration includes links/nodes and their characteristics (e.g. lanes, connectivity, etc.)	A
	SC-8	P	They system shall generate operational scenarios of emerging modes and CAV technologies to be evaluated by the other system components: Demand Changes and Operational Performance.	This includes the operation of new modes on the network, initial market penetrations of CAVs, type of CAV systems deployed)	A
	SC-9	D	The system shall generate and store data on network configurations and operational scenarios of new modes in a format that is accessible by other system components.	Examples: types and locations of wireless telecommunication technology on the network	A
	SC-10	I	The system shall enable the generated system configuration and network characteristics to be accessible by demand models to evaluate activity patterns and travel behavior	Examples: parts of the network where CAV systems are available and predicted/assumed characteristics of emerging modes (SAVs)	A
	SC-11	I	The system shall enable the generated system configuration and network characteristics to be accessible by performance models to evaluate the system performance under the predicted supply conditions	Examples: parts of the network where CAV systems are available and predicted/assumed characteristics of emerging modes (SAVs)	A

Table 2. System requirements for evaluating the strategic impacts of connected and automated systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Demand Changes	DC-1	F	The system shall integrate automated vehicles in the demand models used by this system/framework	Automated vehicles have different characteristics from regular vehicles and demand models should reflect that	A
	DC-2	F	The system shall integrate emerging mobility options in the demand models used by the system/framework.	Examples of emerging modes include Shared-Automated-Vehicle fleets and new multimodal options (Transit + SAV).	A
	DC-3	F	The system shall integrate the multitasking feature enabled by highly automated vehicles.	This is a unique feature that can affect activity patterns at households and businesses	A
	DC-4	F	The system shall assess the impact of CAVs on vehicle ownership at households and businesses.	The ability to easily share automated vehicles may impact vehicle ownership	H
	DC-5	F	The system shall predict the change in the number of household trips at different market penetrations of CAV systems.	With the ability to multitask while riding an automated vehicle service, for example work, people may travel to other places more often.	H
	DC-6	F	The system shall predict the change in the purpose of trips generated from households at different market penetrations of CAV systems.	Example: the change in work or personal trips	H
	DC-7	F	The system shall predict the change in trip durations by CAV modes.	Example: longer durations because of multitasking during trip.	H

Table 2. System requirements for evaluating the strategic impacts of connected and automated systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Demand Changes (cont'd)	DC-8	F	The system shall predict the change in trip chains/sequencing	Example: changes to the start, end, duration of trips and activities.	H
	DC-9	F	The system shall assess the impacts of a robotic "Chauffeur" on household activity prioritization and sequencing	Some activities may go in parallel or their sequence may change using the new service	M
	DC-10	F	The system shall evaluate changes to in-vehicle/out-of-vehicle value of time because of enabled multitasking in automated vehicles	Example: value of in-vehicle travel time may change as it's not totally lost as a result of enabled multitasking in an automated service	M
	DC-11	F	The system shall evaluate mode shifts including multimode use as a result of CAV systems.	Example: shifts to multimodal options such as transit and SAVs.	H
	DC-12	F	The system shall asses land use impacts of CAVs.	Example: potential shifts in residence location and/or businesses.	M
	DC-13	F	The system shall implement dynamic route choice based on detailed information obtained from CAVs.	Connectivity enables more accurate estimation of traffic states that should be reflected in routing models	H
	DC-14	F	The system shall evaluate impacts of CAVs on departure times.	Example: less variable departure due to lower uncertainty in traffic conditions	M
	DC-15	F	The system shall implement new data sources enables by connectivity as well as traditional data sources	Examples of emerging data sources includes GPS and mobile data. Examples for traditional data sources include travel surveys.	H
	DC-16	P	The system shall produce traffic flows on the network to be simulated by performance models	None	A

Table 2. System requirements for evaluating the strategic impacts of connected and automated systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Demand Changes (cont'd)	DC-17	P	The system shall produce summary reports of trip durations, numbers, purposes generated by the transportation system under study.	None	H
	DC-18	P	The system shall produce comparative reports of CAVs impacts on trips and mode choice at different market penetrations	None	H
	DC-19	P	The system shall produce trip and activity information in raw format so that users can perform their own analysis	None	H
	DC-20	D	The system shall have the ability to import all types of data required for the analysis of travel behavior and activity patterns	Examples of data required includes: activity logs, travel surveys, socio-demographic surveys, and land use.	A
Demand Changes (cont'd)	DC-21	I	They system shall enable the generated demand flows and mode choices to be accessible by performance models to evaluate the new system's attributes in the presence of CAV technology at the operational level	None	A

Source: FHWA 2018

A = absolute (essential). CAV = connected and automated vehicle. D = data. F = functional. H = High. I = Integration. M = Medium. P = performance. SAV = shared automated vehicle. V2V = vehicle to vehicle. V2I = vehicle to infrastructure. V2X = vehicle to anything.

System Requirements for Evaluating Operational Performance Impacts of Connected and Automated Vehicle Systems

Table 3 summarizes the high-level system requirements for evaluating the **operational/tactical** impacts of CAV technology. Below is a description of the table's columns:

- Framework Component: groups the requirements according to the main components of the conceptual framework for evaluating the operational performance impacts of CAV systems (see Figure 1).
- Req. ID: the system requirement identification number. (Note: OP refers to Operational Performance.)
- Req. Type: As defined above—Functional (F); Performance (P); Data (D); Integration (I).
- System Requirement: description of the system requirement
- Notes: additional notes related to the system requirement
- Priority: related to the implementation of the requirement. Four priorities were identified:
    1. A: Absolute (Essential).
    2. H: High.
    3. M: Medium.
    4. L: Low.

Table 3. System requirements for evaluating the operational performance impacts of connected and automated vehicle systems.

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Wireless Telecom. and Sensors	OP-1	F	The system shall integrate information flow through V2I/V2V/V2X communications within the AMS system at a practical time scale associated with the time scale for vehicle motion.	Example: message broadcasting at microscale level (0.1 seconds)	A
	OP-2	F	The system shall model different communication network structures for different telecommunication technologies.	Examples: point to point, ad-hoc, and structured network.	H

Table 3. System requirements for evaluating the operational performance impacts of connected and automated vehicle systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Wireless Telecom. and Sensors (cont'd)	OP-3	F	The system shall model different clustering patterns of CAVs based on wireless telecommunication networks	Examples: number of vehicle clusters formed, number of vehicles within clusters, ranges of those clusters, and frequency of updating those structures.	H
	OP-4	F	The system shall model sensor performance and reliability aspects that directly influence vehicle performance	Examples: radar range, positioning, interruptions, packet delivery rates, and connection latency.	A
	OP-5	F	The system shall model the uncertainty associated with CAV's sensor performance.	Examples: probabilistic distributions rather than point measures.	M
	OP-6	F	The system shall integrate as required V2X communications to include other connected road users	Examples: pedestrians and Bicyclists	M
Isolated-Manual Driver Behavior	OP-7	F	The system shall integrate state-of-the-art models to represent car-following behavior (acceleration choice) of isolated human drivers	None	A
	OP-8	F	The system shall integrate state-of-the-art models for representing lane-changing behavior of isolated human drivers	None	A
	OP-9	F	The system shall have the ability to update behavioral models of isolated-manual drivers (car-following and lane changing) as improved models becomes available or new data becomes available	Example: update car-following models	A

Table 3. System requirements for evaluating the operational performance impacts of connected and automated vehicle systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Isolated-Manual Driver Behavior (cont'd)	OP-10	F	The system shall have the ability to calibrate/recalibrate model parameters of isolated-manual driving based on actual trajectory data.	None	A
Connected-Manual Driver Behavior	OP-11	F	The system shall integrate state-of-the-art models to represent car-following behavior (acceleration choice) of connected human drivers, distinct from isolated driving behavior.	None	A
	OP-12	F	The system shall integrate state-of-the-art models for representing lane-changing behavior of connected human drivers, distinct from isolated driving behavior.	None	A
	OP-13	F	The system shall have the ability to update behavioral models of connected human drivers (car-following and lane changing) as improved models becomes available.	None	A
	OP-14	F	The system shall have the ability to calibrate/recalibrate model parameters of connected-manual driving as actual trajectories become available	None	A
	OP-15	F	The system shall model the different effects of telecommunication technologies on connected drivers.	Example: effect of vehicle movement information via V2V vs. the effect of traffic condition information via V2I	H

Table 3. System requirements for evaluating the operational performance impacts of connected and automated vehicle systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Connected-Manual Driver Behavior (cont'd)	OP-16	F	The system shall integrate basic attributes for modeling the effectiveness of connected systems.	Examples: driver compliance rate, driver response delay, and driver response accuracy.	A
	OP-17	F	The system shall have the ability to update effectiveness attributes of connected systems as actual data become available	Example: data obtained from connected vehicles on the road or simulated connected driving environment	H
Isolated-Automated Driving Behavior	OP-18	F	The system shall integrate state-of-the-art models to represent car-following behavior (acceleration choice) of the different levels of automated driving behavior (Level 1, 2, ..., 5) without communication capabilities.	None	A
	OP-19	F	The system shall integrate state-of-the-art models for representing lane-changing behavior of the different levels of automated driving behavior (Level 1, 2, ..., 5) without communication capabilities.	None	A
	OP-20	F	The system shall have the ability to update the robotic driving behavior as more information about the control algorithms used in automated vehicles becomes available	Example: control logic used by OEMs.	A
Connected-Automated Driving Behavior	OP-21	F	The system shall integrate state-of-the-art models to represent car-following behavior (acceleration choice) of the different levels of automated driving behavior (Level 1, 2, ..., 5) with communication capabilities.	None	A

Table 3. System requirements for evaluating the operational performance impacts of connected and automated vehicle systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Connected-Automated Driving Behavior (cont'd)	OP-22	F	The system shall integrate state-of-the-art models for representing lane-changing behavior of the different levels of automated driving behavior (Level 1, 2, ..., 5) with communication capabilities.	None	A
Heterogeneous Traffic Interactions	OP-23	F	The system shall model multilane interactions among drivers.	Examples: moving to restricted lanes or HOV lanes.	A
	OP-24	F	The system shall simulate mixed-traffic conditions for different CAV market penetrations and capture the interactions among different driving behaviors.	Example: simulate the interactions of connected, automated, and human vehicles on the road	A
	OP-25	F	The system shall simulate various operational interventions, traditional and emerging via CAV systems.	Examples of such interventions include speed harmonization, queue warning, ramp metering, and HOV lanes.	A
	OP-26	F	Simulate the interactions between drivers (isolated, connected, and automated), pedestrians, and bikers at signalized intersections.	None	H
	OP-27	F	The system shall simulate emerging traffic signal control algorithms that use data generated from CAV systems.	Example of such control systems include Eco Approach and Departure, Emergency Vehicle Preemption, and Transit Signal Priority.	A

Table 3. System requirements for evaluating the operational performance impacts of connected and automated vehicle systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
Heterogeneous Traffic Interactions (cont'd)	OP-28	F	They system shall use new data sources obtained from CAV systems as well as traditional data sources (e.g. loop detectors)	Examples of new data obtained by CAVs: detailed vehicle trajectories, speeds, and accelerations. Traditional data sources: counts from loop detectors and mean speeds from radars.	A
General	OP-29	F	The system shall evaluate all types of transportation facilities.	Examples: networks, freeways, corridors, highways, and rural roads.	A
	OP-30	F	The system shall integrate external operational conditions and simulate their effect on the transportation system performance under different scenarios.	The external operational conditions include: weather, incidents, special events, work zone, and saturated/high demand.	A
	OP-31	P	The system enable users to define different operational scenarios to be simulated	Examples: market penetration, flow, external conditions.	A
	OP-32	P	The system shall produce multiple system attributes to evaluate CAV impacts	Examples: travel time, reliability, and comfort.	A
	OP-34	P	The system shall produce multiple performance measures for evaluating CAV impacts,	Examples: metrics related to safety, throughput, flow stability, and sustainability	A
	OP-35	P	The system shall produce raw performance data for users to calculate their own performance measures	Examples: vehicle trajectory data, traffic control data, and communication messages.	A
	OP-35	D	The system shall store performance data of simulated vehicles	Examples: vehicle trajectory data, traffic control data, and communication messages.	A

Table 3. System requirements for evaluating the operational performance impacts of connected and automated vehicle systems. (continued)

Framework Component	Req. ID	Req. Type	System Requirement	Notes	Priority
General (cont'd)	OP-36	I	The system shall integrate the demand patterns and network configuration produced at the strategic level to evaluate the operational performance impacts of CAVs	Examples: communication technology and demand flows on the network	A
	OP-37	I	The system shall enable the generated system attributes to be accessible by demand models to update mode characteristics	Example: travel time	A

Source: FHWA 2018

A = absolute (essential). CAV = connected and automated vehicle. D = data. F = functional. H = High. I = Integration. M = Medium. P = performance. SAV = shared automated vehicle. V2V = vehicle to vehicle. V2I = vehicle to infrastructure. V2X = vehicle to anything.

Chapter 4. Review of Prior and Current Work

This chapter provides an overview of related literature, reports, and planned activities relating to analysis, modeling, and simulation for connected and automated vehicles. The materials reviewed in this chapter serve to identify the main gaps in literature where current capabilities are insufficient or do not meet the user needs as identified in the Task 3 reports: Concept of Operations and System Requirements. (*6; 80*)

Supply-related Impacts of Connected And Automated Vehicle Technology – Modeling Shared Automated Vehicle Fleets

The new capabilities and attributes of connected and automated vehicles (CAVs) can create entirely new mobility options (*26*). One such option is shared automated vehicle (SAV) fleets. Shared-automated-vehicle systems, also known as e-Taxis, are a new form of mobility enabled by CAV technology. The system's potential improvements over human-driven taxis and ride-hailing systems include lower costs (because driver-related expenses no longer apply) and a safer trip (because human error is eliminated from the driving process). In addition, for some travelers the new mode can remove the need for personal vehicles.

Some papers in the literature studied SAV modeling as a special case of fleet management problems (*59*). Other papers proposed frameworks for modeling SAVs through event-based simulation (*60; 61*) or used network-level agent-based simulations (*54; 56*) to evaluate their impacts. Table 4 provides a summary of selected papers that are related to SAV modeling which are discussed in the remaining of this section.

Table 4. Summary of papers related to shared-automated-vehicle modeling.

Study	Model	Data/Testing	Major Findings
Hyland and Mahmassani (*59*)	Taxonomy of shared-automated-vehicle (SAV) management problems	Conceptual, literature	The automated vehicle (AV) fleet management problem is a dynamic, multi-vehicle pickup and delivery problem with explicit or implicit time-window constraints wherein the isolated-automated vehicles (AV) fleet manager has global information

Table 4. Summary of papers related to shared-automated-vehicle modeling. (continued)

Study	Model	Data/Testing	Major Findings
Levin et al. (*60*)	Event-based framework for modeling SAV vehicles where the first event introduces demand and the second event dispatch SAVs to fulfil that demand	Network of Austin, Texas	Using SAVs without dynamic ride-sharing increases travel time compared to personal vehicles and that effective routing heuristics and the right fleet size is required for SAV to effectively replace personal vehicles
Fagnant and Kockelman (*56*)	Agent-based simulation	Network of Austin, Texas	Dynamic ride sharing can reduce total service time and travel costs of SAV users, even after accounting for extra passenger pick up, drop offs, and non-direct routing
Chen et al. (*54*)	Agent-based simulation for shared-automated-electrical vehicles (SAEV)	Hypothetical gridded city	The number of private vehicles that can be replaced by SAEVs depends on the electric vehicles range and the infrastructure charging speed
Mendes et al. (*61*)	Event-based simulation comparing SAV to light rail	Proposed light rail line connecting Brooklyn and Queens in New York City	Demand responsive shared-automated-vehicle fleet of 150 vehicle is required to replace the 39 cars of the light rail system and that the total travel time of the SAV is 36% less than that of light rail

Source: FHWA 2018

Hyland and Mahmassani (*59*) presented a taxonomy to classify vehicle fleet management problems to inform future research on automated vehicle fleets. The authors classified AV fleet management problems using existing categories in literature and included additional categories specific to automated vehicles. The taxonomy is summarized in Table 5. The first column in the table includes taxonomic categories existing in literature that were used in the paper to broadly define AV fleet management problems. The underlined categories in the table signify that the AV fleet management problem is a dynamic, multi-vehicle pickup and delivery problem with explicit or implicit time-window constraints wherein the AV fleet manager has global information. The second column shows other categories in the literature that are relevant to AV management fleets. The third column in the table shows novel taxonomic categories presented in the paper to classify AV fleet management problems. For more information on the taxonomic classifications, refer to the original paper by Hyland and Mahmassani (*59*).

Table 5. Taxonomy of automated vehicle fleet management problems.

<table>
<tr><th colspan="2">Existing Taxonomic Categories</th><th rowspan="2">Novel Taxonomic Categories</th></tr>
<tr><th>Classifying the General AV Fleet Management Problem</th><th>Remaining Taxonomic Categories to Classify Specific AV Fleet Management Problems</th></tr>
<tr>
<td>Pickup and/or Delivery
• Pickups only
• Deliveries only
• Pickups and deliveries
Evolution of Information
• Static
• Dynamic
Availability of Information
• Global
• Local
Time-Window Constraints
• No time-windows
• Explicit time-windows
• Implicit time-windows
• Explicit and implicit
Size of Vehicle Fleet
• One vehicle
• Multiple vehicles</td>
<td>Quality of Information
• Deterministic
• Stochastic
Processing of Information
• Centralized
• Decentralized
Vehicle Homogeneity
• Homogenous
• Heterogeneous
Location of Demands
• Nodes
• Arcs
• Mixed
Arc Directionality
• Directed
• Undirected
• Mixed
Vehicle Capacity Constraints
• Imposed all the time
• Imposed some of the time
• Not imposed
Maximum vehicle route times (and distances)
• Imposed – all the same
• Imposed – not all the same
• Not imposed
Costs
• Variable or routing costs
• Fixed operating or vehicle acquisition costs (capital costs)
Objective
• Maximize profit
• Minimize cost
• Minimize client inconvenience
• Minimize vehicle miles traveled
• Minimize traveler wait time
• Minimize traveler in-vehicle travel time
• Minimize number of vehicles</td>
<td>Fleet Size Elasticity
• Elastic
• Fixed Fleet Size
Reservation Structure
• Short-term rentals
• Point-to-point service
• Mixed
Pricing
• No pricing
• Fixed pricing structure
• Pricing, with no fixed structure
Accept/Reject Decision
• No decision
• Fleet manager decision
• Customer decision
Reservation Timeframe
• Immediate requests
• Minimum pre-reservation time
• Mixed
Repositioning
• No repositioning
• Repositioning based on stochastic information
Underlying Network
• Real road network
• Test road network
• Graph/Virtual Network
Network Congestion
• No congestion
• Static
• Time-dependent</td>
</tr>
</table>

Source: Hyland, M. F., and H. S. Mahmassani. 2017. Taxonomy of Shared Autonomous Vehicle Fleet Management Problems to Inform Future Transportation Mobility. *Transportation Research Record: Journal of the Transportation Research Board*, 2653: 26-34.
AV = isolated-automated vehicles.
Note: Underlined categories in the table signify that the AV fleet management problem is a dynamic, multi-vehicle pickup and delivery problem with explicit or implicit time-window constraints wherein the AV fleet manager has global information.

Several studies explored different possibilities for modeling SAV fleets. Levin et al. (*60*) proposed a general framework for modeling SAVs that is built on two main events that can be integrated with most traffic simulation models: 1) demand and 2) SAV dispatcher. The demand module introduces demand into the simulation in the form of travelers requesting SAVs at each time step of the simulation. Those travelers can be either individuals or groups of people traveling together. The SAV dispatcher module assumes that a central dispatcher, with full information on all available SAVs through wireless telecommunication, assigns vehicles and routes to travelers. The dispatcher module outputs SAV trips passed to the simulation module. Finally, the traffic simulator module uses the SAV trips generated by the dispatcher and determines their arrival time at the destinations.

The authors implemented the framework on a dynamic traffic assignment simulator and examined a scenario in which SAVs replace personal vehicles in the downtown Austin network. The results showed that using SAVs without dynamic ride-sharing (pooling multiple travelers with same origins, destinations, and travel times in the same vehicle) increases travel time compared to personal vehicles, and that a much larger fleet is needed for the AM period. However, dynamic ride-sharing significantly reduced travel time by combining travelers' trips. Their conclusion was that, with effective routing heuristics and the right fleet size, SAVs could effectively replace personal vehicles.

In another study, Fagnant and Kockelman (*56*) explored the potential impacts of dynamic ride sharing for a system of SAV using agent- and network-based simulation platforms. The authors tested their models on Austin's network. Their results showed that dynamic ride sharing can reduce both total service time and travel costs for SAV users, even after accounting for extra passenger pick ups, drop offs, and non-direct routing. The results also showed that total VMT increases as SAV membership increases, and dynamic ride sharing (DSR) users become more flexible with timing and routing.

Motivated by potential synergies between automated vehicles and electric vehicle technologies, Chen et al. (*54*) analyzed the operation of shared-automated-electric-vehicle (SAEV) systems using an agent-based simulation tool under various vehicle ranges and charging infrastructure scenarios in a gridded city. Their results showed that the number of private vehicles that can be replaced by SAEVs depends on the electric vehicles' range and the infrastructure charging speed. For example, simulations showed that an SAEV with an 80-mile range can replace 3.7 privately owned vehicles while an SAEV with a 200-mile range can replace 5.5 privately owned vehicles under Level II (240-volt AC) charging. With fast charging (Level III, 480-volt DC), ratios increase to 5.4 and 6.8 privately owned vehicles replaced by SAEVs with an 80-mile range and a 200-mile range, respectively.

Furthermore, a financial analysis performed as part of the study implies that the SAEV service can be offered at an equivalent rate to privately owned vehicles for low-mileage households, making it a competitive alternative to current manually driven car sharing services and on-demand driver operated transportation services. As for vehicle miles traveled (VMT), results suggest that the SAEV service generated 7.1 percent to 14.0 percent additional VMT due to the need to travel empty miles for charging and passenger pick up. The percentages are lower, however, for cities with more concentrated origin-destination patterns, as in the case of Austin, Texas.

In a related work, Mendes et al. (*61*) compared a SAV fleet system to a proposed light rail line connecting Brooklyn and Queens in New York City. The authors used an event-based simulation model to compare the performance of both systems under the same demand patterns and operating speeds. Their results show that a demand responsive SAV fleet of 150 vehicles is required to replace the 39 cars in the light rail system and that the total travel time for the SAVs is 36 percent less than that of light rail.

Demand-related Impacts of Connected and Automated Vehicle Technology

The new forms of mobility and enhancements that CAV technologies bring to current transportation systems could affect demand patterns on different levels. At the macro level, vehicle ownership in households will be affected as automated vehicle technology can make sharing vehicles more efficient and convenient. This can lower the number of vehicles needed by households or eliminate the need for it altogether, if the new service is proved to be reliable and financially competitive.

At a moderately granular level, activity patterns of households can be affected by the new technology. Allowing multitasking while being driven in automated vehicles may change the value of in-vehicle time. People may travel longer distances as they would be able to do some tasks while driving, like working or watching a movie. Furthermore, having a robotic “chauffeur” to assist in daily chores can reprioritize activities in the household. For instance, highly automated vehicles could pick up kids from school or groceries from the store.

At the micro level, travel routes, mode choice, and departure times can be affected by CAV systems. Connectivity, for example, can impact route choice through sharing traffic conditions between vehicles or between vehicles and the infrastructure, leading to better estimates of travel times and shortest paths. In addition, automated vehicles can dynamically reroute themselves as they receive more information about network traffic conditions.

In addition to route choice, new mobility options will affect mode choice by travelers. As connectivity would allow better integration between modes, travelers may choose to use multiple modes simultaneously, like using ride-sourcing and transit, or shift entirely to different modes.

To model demand changes caused by CAV technology, a different set of tools and frameworks from the traditional ones used to date must be developed. These tools need to incorporate new assumptions and behaviors related to CAV technology. Maren Outwater (*1*), in her review of such efforts, outlines different methods used by researchers for integrating CAV technology into models. Those include models of vehicle choice, strategy, activity-based models, and the four-step models. Those different methods are discussed further in the review of current/prior work in the following subsections.

Forecasting Adoption of Connected and Automated Vehicle Technologies

CAV systems promise significant improvements to road safety, mobility, and sustainability. As a result, researchers, manufacturers, and policy makers are all interested in forecasting the adoption of CAV systems to ensure that their decisions support future deployment of the new technology. However, forecasting the CAV adoption rate is a complex problem with many factors to consider on both the demand and the supply sides (*81*); for example, one such factor is the extent to which travelers are willing to pay for new features and the technology price itself (*81*). Nonetheless, some researchers and industry professional have made various predictions about CAV technology adoption rates.

Previous research predicted the adoption rate of the new technology and the characteristics of users who are likely to use it using different approaches. Some studies compared the deployment of CAV systems to previous new technology deployments—such as automatic transmission (*27*) and hybrid electric vehicles (*28*)—or used network-level simulations (*81*). Other studies conducted stated-preference surveys to characterize adopters of the new technology (*35; 82*). The differences show that high CAV adoption rates are not likely to occur before 2060 and that early adopters are likely to be young, educated, tech-oriented adults. Table 6 provides a summary of the selected papers discussed next.

Table 6. Summary of selected studies on connected and automated vehicle technology adoption.

Study	Model	Data/Testing	Major Findings
Litman (*27*)	Comparison to previous vehicle technology deployment	Historical data for previous technology deployment	Connected and automated vehicle (CAV) market penetration will follow the automatic transmission deployment pattern, taking up to five decades to achieve saturation without a government mandate
Lavasani (*28*)	Generalized Bass diffusion models	Historical sales of Hybrid Electric Vehicles in the US; Demographic data	Assuming isolated-automated vehicle (AV) sales start in 2025, market will be saturated in 2059
Bansal and Kockelman (*81*)	Agent-based simulation	U.S. survey on public acceptance of CAV	98% of vehicle fleets in the U.S. will have connectivity in year 2030; light-duty vehicle fleets will have 25%-87% adoption rate by 2045 depending on willingness to pay and cost of technology
Lavieri et al. (*82*)	Generalized Heterogeneous Data Model; Structural equations	Puget Sound Regional Travel Study, 2014-2015	Younger urban residents who are more educated and tech-savvy are more likely to be early adopters of automated vehicle technologies, favoring a sharing-based service model over private ownership
Haboucha et al. (*35*)	Logit Kernel choice model of autonomous vehicles	Stated preference survey on autonomous vehicles	Early adopters are likely to be young educated individuals who spend a lot of time in their vehicles

Source: FHWA 2018

Litman (*27*), in his report on automated vehicle implementation predictions, used previous vehicle technology deployments, such as airbags, automatic transmission, and hybrid vehicles, to project the implementation of CAV systems. Litman's projections assumes that fully automated vehicles will be available for sale by 2020 for a high price and with imperfect technology. The market share will continue to go up as the technology becomes more mature and the price drops. The report projects that high market penetration rates will follow the automatic transmission deployment pattern, taking up to five decades to achieve saturation without a government mandate.

Adopting a similar concept but using a more rigorous quantitate approach, Lavasani (*28*) developed an AV market penetration model that is based on previous technology adoption trends including hybrid electric vehicles and cellphones. The authors used Generalized Bass diffusion models, a type of hazard functions, which calculates the probability that adoption will occur at specific year given that it has not yet occurred. To build the model, the authors selected two values representing the innovation factor (risk taking capacity) and the imitation factor (culture and life style preferences) and addition to external variables including estimated price of AV compared to regular vehicles and economic wealth. As for the market size, potential number of adopters, the authors assumed that 75 percent of households' potential adopters based on internet usage. Their results show that, assuming AV sales start in 2025, 1.3 million vehicles will be sold in next five years after sales start and that the number will increase to 36 million in 10 years. The model also shows that the market will be saturated in 2059 which confirms the projections of Litman (*27*).

In another study by Bansal and Kockelman (*81*), the authors proposed a simulation-based framework to estimate the long-term adoption rates of CAV systems. The framework consists of multiple stages pursued together at a one-year interval. The first stage of the framework is vehicle transaction and technology adoption model that simulates households' decisions to buy, sell, replace vehicles, or add CAV technology to old ones. In the following step, CAV technologies are added to vehicles if the price of the technology is less than the willingness to pay[2] (WTP) among households.

The authors used the fleet evolution framework to forecast Americans' long term (2015-2045) adoption rates of CAV technology under different scenarios. The scenarios were defined based on annual technology price drops (5 percent, 10 percent) and annual increments in Americans' WTP (0 percent, 5 percent, and 10 percent). The simulations were calibrated by data obtained from a survey of 2,167 Americans regarding their perception of CAVs and their household vehicle transactions. Their results suggest that 98 percent of vehicle fleets in the United States will have connectivity in year 2030 under NHTSA's probable regulations. In addition, light-duty vehicle fleets will have a 25 percent to 87 percent adoption rate by 2045, depending on the assumed incremental change in WTP and decreases in price.

Lavieri et al. (*82*) presented a comprehensive model system of autonomous vehicle adoption and use built on data collected as part of the Puget Sound Regional Travel Study. Their results showed that lifestyle factors play an important role in shaping autonomous vehicle usage. Younger urban residents who are more educated and tech-savvy are more likely to be early adopters of autonomous vehicle technologies, favoring a sharing-based service model over private ownership.

Similarly, Haboucha et al. (*35*) built a choice model of autonomous vehicles to predict the adoption of the new mode using data collected from a stated preference survey in Israel and North America. Their results show that a large hesitation towards the new mode currently exists, with 44 percent

[2] "Willingness to pay" is defined as the the most a consumer will spend on one unit of a good or service. See *Market Business News*, Financial Glossary (2018), s.v. "willingness to pay."

of surveyed individuals choosing to use regular cars, while early adopters are likely to be young, educated individuals who spend a lot of time in their vehicles.

Travel Mode Shifts due to Automated Vehicles

The anticipated benefits and functionalities of highly automated vehicles can put this technology in a travel mode of its own. The new mode offers flexibility with origin-destination points in addition to providing passengers with the ability to multitask during the trip, making productive use of the time spent in transit. This new feature of being able to be productive while commuting in a private car may change perceptions and the value of time spent commuting (*29*). In addition, recent research (*83*) suggests that being driven by a robot can be less stressful than piloting a vehicle.

The literature approached the question of mode shift by modifying existing demand models and adding highly automated vehicles as a new mode. The characteristics of the new vehicles, and the sensitivity of users to attributes like costs and time, were derived from other studies. The literature also performed sensitivity analyses using different assumed values. Table 4 provides a summary of selected papers that tried to answer questions regarding mode shift, which will be further discussed below.

Table 7. Summary of selected studies on mode shift due to the introduction of connected and automated vehicle technology.

Study	Model	Data/Testing	Major Findings
Childress et al. (*83*)	Seattle region's activity-based model	Isolated-automated vehicles (AV) mode characteristics are based on findings of previous studies	High AV market penetrations will reduce transit share by 9% and walk share by 21%
LaMonida et al. (*34*)	Trip generation and choice models	Michigan State's 2009 Long-Distance Travel Survey	Travelers equally shift from airlines and personal vehicles to automated vehicles by 25% - 37%.
Perrine et al. (*36*)	Modified travel demand model, rJourney	long-distance trips traveled throughout the united states in 2010	AV mode causes 53% shift in number of air trips towards the new mode and personal vehicles

Source: FHWA 2018

A study by Childress et al. (*83*) modified the Seattle region's activity-based model to explore the potential travel impacts of automated vehicles. The study defined different scenarios based on expected improvements in road capacity and changes to perceived travel time and parking costs. Results showed that, in a scenario of high AV market penetration rates (modeled as a 30 percent increase in road capacity), impacts included a 65-percent reduction in perceived travel time and a 5-percent reduction in parking cost. In terms of the distribution of travelers by mode, the result was a decrease in the transit share of around 9 percent and a decline in the pedestrian share of 21 percent.

Another study by LaMonida et al. (*34*) investigated potential long-distance travel mode shifts due to automated vehicles. To do so, the study analyzed the Michigan State's 2009 Long-Distance

Travel Survey, developed a long-distance trip generation and mode-choice models, and applied those models in a statewide simulation experiment. The new AV mode in the models is assumed to have a lower perceived en-route travel time and higher cost, reflecting initial deployment of the new system. The simulation experiments highlighted potential mode shifts across different trip distances and purposes. The three modes analyzed were personal vehicles, airlines, and the newly introduced automated vehicles.

Simulation results showed that for distances less than 500 miles, travelers equally shift from airlines and personal vehicles to automated vehicles by 25 percent to 37 percent. The shift percentage increases as travel distance decreases. Beyond 500-miles, the percentage shift to automated vehicles is consistently around 20 percent for personal vehicles, although it drops dramatically in favor of airlines as distances increase, indicating flying is still preferred for very long distance travel. The model also showed that as the AV costs increase and the perceived benefit over other modes decreases, the likelihood of shifting to the new mode decreases. Nevertheless, cost becomes less important as the perceived benefits in travel time increase.

Perrine et al. (*36*) also studied potential mode shifts for long distance travel due to the availability of self-driving cars. The authors modified an existing travel demand forecasting model, rJourney, by adding AV as an additional mode in addition to rail, air, and private cars. The original model is based on 1.17 billion long-distance trips traveled throughout the United States in 2010. The results show that the addition of the AV mode severely affects air travel, with the number of trips dropping by 53 percent. The model also shows that the introduction of the AV mode affects the destination choice as the total miles traveled increased by 9.6 percent for personal vehicles while it was reduced by 6.7 percent for all other modes.

Impact of Automated Vehicles on Vehicle Ownership

One of the potential demand pattern changes entailed by the introduction of CAV-enabled mobility options is household vehicle ownership. The automated vehicle technology will make sharing vehicles more efficient and convenient (*57*). Households, therefore, may require fewer owned vehicles since those vehicles can drive themselves and efficiently serve multiple members of the households. Furthermore, new shared-automated service may even eliminate the need to own a vehicle all together if the service proves to be reliable and cost effective. This is indicated also by recent research on current car-sharing programs which shows that the service can potentially reduce vehicle ownership if users perceive it as a cost effective, environmentally friendly (*84*), and easily accessible option (*51*). Former studies tried to evaluate CAV impacts on vehicle ownership by directly asking travelers in the form of stated preference surveys (*55*) or by developing simulation platforms with SAV service (*53; 54*). Table 8 provides a summary of selected studies which are discussed next.

Table 8. Summary of selected studies on CAV impacts on vehicle ownership.

Study	Model	Data/Testing	Major Findings
Schoettle and Sivak (*52*)	Descriptive analysis	National Household Travel Survey	43% reduction can be achieved in household vehicle ownership by sharing a vehicle for all non-overlapping trips, which accounts for 84% of total household trips

Table 8. Summary of selected studies on CAV impacts on vehicle ownership. (continued)

Study	Model	Data/Testing	Major Findings
Fagnant and Kockelman (*53*)	Agent-based simulation	Hypothetical gridded network	One SAV can replace around eleven conventional vehicles
Chen et al. (*54*)	Agent-based simulation, Electric SAV	Hypothetical gridded network	An 80-mile range SAEV can replace 3.7 privately owned vehicles while a 200-mile range SAEV can replace 5.5
Zmud et al. (*55*)	Descriptive analysis	Consumer acceptance survey and interviews	61% of respondents in the study indicated that the number of cars they own won't change if automated cars were available today

Source: FHWA 2018
SAEV = shared-automated electric vehicle. SAV = shared-automated-vehicle.

In order to quantify the potential reduction in household vehicle ownership due to sharing automated vehicles, Schoettle and Sivak (*52*) analyzed the latest National Household Travel Survey data. They found that 83.7 percent of households had no trips that overlapped or conflicted, opening the possibility of reducing the number of vehicles owned by sharing an automated vehicle to serve those non-overlapping trips. In the most extreme hypothetical scenario, a 43 percent reduction can be achieved in household vehicle ownership by sharing a vehicle for all non-overlapping trips, resulting in a 75 percent increase in vehicle usage (not including extra miles generated by the return-to-home trip). The authors stressed in their report, however, that many other factors affect the adoption of automated vehicles and that the above-mentioned numbers should be considered as upper bounds.

In another study, Fagnant and Kockelman (*53*) designed an agent-based simulation model to evaluate the travel and environmental implications of SAV fleets for multiple operational scenarios. The model generates trips through a grid network, with each point assigned an origin, destination, and departure time. The model first estimates the number of SAVs required to serve generated trips then utilizes multiple routing strategies to minimize future travelers' waiting time. The model was used to simulate multiple case studies with varying trip generation rates, network congestion, trip distribution, and service areas. Their initial results indicate that one SAV can replace around 11 conventional vehicles; however, this adds around 10 percent more travel distance than comparable non-SAV trip.

A study by Chen et al. (*54*) examined the operation of SAEV systems using an agent-based simulation model. Results showed that the number of private vehicles that can be replaced by SAEVs depends on the electric vehicles range and the infrastructure charging speed. For example, simulations showed that an SAEV with an 80-mile range can replace 3.7 privately owned vehicles, while an SAEV with a 200-mile range can replace 5.5 privately owned vehicles under Level II (240-volt AC) charging. With fast charging (Level III, 480-volt DC), ratios increase to 5.4 and 6.8 privately owned vehicles replaced by SAEVs with an 80-mile range and with a 200-mile range, respectively.

A recent report by Zmud et al. (*55*) on the consumer acceptance of automated vehicles shows that the majority of the 44 respondents interviewed (61 percent) in the study indicated that the number of cars they own would not change if automated cars were available today, whereas 23 percent indicated that they would reduce the number of cars they own. A small but meaningful percentage (16 percent) indicated that they would increase the number of cars owned.

Impact of Automated Vehicles on Vehicle Miles Traveled

The new capabilities of highly automated vehicles can impact vehicle miles traveled (VMT) in a variety of ways. The ability of passengers to multitask during a trip in an AV may reduce the perceived (negative) value of time-in-travel for travelers, may make travelers less averse to longer trips, and therefore, increase overall VMT. Additionally, the chauffeur-like function of AVs may add more traveled distance if a vehicle, for example, travels back home after dropping off a traveler at the designated destination. Furthermore, the new technology may attract new types of travelers who cannot drive, like children and the elderly (*30*), adding even more trips to the network. SAVs can also travel longer distances due to the need to relocate between trips.

Previous studies in the literature evaluate the impacts of AVs on VMT by modifying existing activity-based models (*83; 85*), four-step models (*33*), or through agent-based simulation (*54*). Some studies examined the impacts qualitatively by relating the new technology to other technology deployments (*27*) or through stated preference surveys (*55*). While all of the studies agree upon the conclusion that AVs are likely to increase VMT, the amount of that increase differs among the studies. This is mainly due to the different assumptions made in the studies about the characteristics of the new mode, such as value of travel time, cost, and road capacity improvements. Therefore, most studies defined different scenarios in which AVs operate and predicted a range of VMT impacts.

Table 6 provides a summary of selected studies on the AV impacts on VMT, which are discussed further later in the section.

Table 9. Summary of selected studies on the impacts of automated vehicles on vehicle miles traveled.

Study	Model	Data/Testing	Major Findings
Bierstedt et al. (*31*)	Related the potential increase in VMTs to the improved driving experience enabled by automation	NHTSA definitions of vehicle automation, judgement call	35% VMT increase per capita at at 95% AV market penetration
Litman (*27*)	Comparison to previous vehicle technology deployment	Historical data for previous technology deployment	AVs are likely to increase VMT
Childress et al. (*83*)	Seattle region's activity based model	AV mode characteristics are based on findings of previous studies	4% to 20% increase in total VMT depending on market penetration
Kim et al. (*85*)	Modified Atlanta regional activity based model	AV mode characteristics are based on findings of previous studies	3.6% to 23.9% increase in daily VMT depending on AV potential benefits to capacity and travel time, at 100 MPR

Table 9. Summary of selected studies on the impacts of automated vehicles on vehicle miles traveled. (continued)

Study	Model	Data/Testing	Major Findings
Auld et al. (*32*)	Modified POLARIS activity based model	Chicago, Illinois network	1% to 78% total VMT increase depending on the scenario and benefits assumed
Zhao and Kockelman (*33*)	Modified four-step model	Existing model for Austin, Texas	18% to 29% VMT increase depending on assumed value of time and operating costs
Chen et al. (*54*)	Agent-based simulation, Electric SAV	Hypothetical gridded network	7.1% to 14.0% additional VMT depending on vehicle range and charging infrastructure configuration
Zmud et al. (*55*)	Descriptive analysis	Consumer acceptance survey and interviews	66% of respondents indicated that their annual VMT would not change
Stephens et al. (*64*)	Descriptive analysis; Estimating upper/lower bounds of VMT impacts	Review of findings in the literature	enormous uncertainty in the effect of CAV on VMT for full automation scenarios

Source: FHWA 2018

AV = isolated-automated vehicle. CAV = connected and automated vehicles. NHTSA = National Highway Traffic Safety Administration. SAV = shared-automated-vehicle. VMT = vehicle miles traveled.

In their report on the effects of next-generation vehicles, Bierstedt et al. (*31*) related the potential increase in VMT to the improved driving experience enabled by automation. The authors argue that a better driving experience (i.e., one with less stress, in-vehicle entertainment or productive activities) may cause vehicle owners to travel more. With higher automation leading to a better driving experience, automation levels 4 and 5 have a higher impact on VMT than lower automation levels that require the constant attention of drivers. They estimate the VMT increase per capita at 35 percent.

Litman (*27*), in his study on automated vehicle predictions, agrees with the argument in the above-mentioned report that more convenient and productive travel will induce higher total VMT on the network. In addition, AVs will make it possible for non-drivers to use this mode and for self-driving taxis to travel more on backhauls.

Childress et al. (*83*) used a modified activity-based model for the Seattle region to explore the potential travel impacts of automated vehicles. The results showed that AV technology increased total VMT by between 4 percent and 20 percent for all scenarios. Vehicle-hours-traveled (VHT), however, increased only in the case where the costs of induced demand are much higher than the benefits of higher capacity, leading to increased average travel time. In other simulated cases, however, the capacity improvements on the network are shown to outweigh the costs of induced demand and results in an overall improvement in travel time.

Kim et al. (*85*) adopted a similar approach to Childress et al. (*83*) by modifying the activity-based model for the Atlanta region to include a Level 4 AV mode at 100 percent market penetration. The authors simulated different scenarios based on assumed potential improvements of the AV technology to road capacity (50 percent increase), in-vehicle time disutility (50 percent decrease), operational costs (71 percent decrease), and parking costs (0 costs at destination). The results show that, for the different scenarios, the total number of trips increase from 0.8 percent to 2.6 percent and that daily VMT increase from 3.6 percent to 23.9 percent over the base scenario with regular vehicles.

Auld et al. (*32*) also used an activity-based model to evaluate CAV-related impacts on travel demand in the city of Chicago, Illinois. Similar to the above-mentioned studies, the authors simulated multiple scenarios based on varying assumptions with regard to the potential benefits of CAV systems. Those assumed benefits are measured by road capacity improvements, CAV market penetration levels, and improved value of travel time. The simulation results show that total VMT increased by 1 percent to 78 percent depending on the scenario and benefits assumed. The results also show that a reduction in value of time has a more significant impact on VMT than the potential capacity increase resulting from increased CAV market penetration rates.

Zhao and Kockelman (*33*) implemented a different approach in their study to evaluate the impact of connected and automated vehicle system on VMT. They modified an existing four-step model for the Austin region in Texas to introduce two new travel modes: private CAVs and shared AVs. For the mode choice step, the authors used a simplified Multinomial Logit model with four mode choices: (Auto, CAV, SAV, and BUS). The authors tested multiple scenarios based on different assumptions regarding the key parameters in the model, including value of travel time, parking costs, CAV operating costs, and SAV operating costs. Their results show that VMT increases by 18 percent to 29 percent when the new CAV modes are introduced.

Chen et al. (*54*) analyzed the operation of shared-automated-electric-vehicle (SAEV) systems using an agent-based simulation tool under various vehicle ranges and charging infrastructure scenarios for a gridded city. The simulation results showed that the SAEV service generates 7.1 percent to 14.0 percent increase in VMT due to the need to travel empty miles for charging and passenger pick up. The percentages are lower, however, for cities with more concentrated origin-destination patterns, as in the case of Austin, Texas.

Zmud et al. (*55*), in a recent report, interviewed a sample of travelers and asked them whether their annual vehicle miles traveled would change if self-driving vehicles were available today. The majority of respondents (66 percent) indicated that their annual VMT would not change, while 25 percent of respondents indicated that it would increase. Of course, it is not clear that typical respondents fully understand that empty vehicle trips generated by their travel would be part of their VMT.

Stephens et al. (*64*) estimated the upper and lower bounds of the CAV impacts on vehicle miles traveled for four different scenarios: 1) Base with no automaton nor connectivity, 2) Partial: with partial automation and some connectivity, 3) Full-No Rideshare: with full automation and high connectivity but no rideshare, and 4) Full-With Rideshare: with full automation, high connectivity, and rideshare. The upper and lower bounds were defined using the highest/lowest potential VMT impacts for each scenario that were reported in previous studies in the literature. Their analysis reveals considerable uncertainty in the effect of CAVs on VMT for full automation scenarios, which reflect the wide range of assumptions used in the literature about the behavior of the new system in the absence of actual data.

Operation-related Impacts of Connected and Automated Vehicle Technology

This section provides a review on some of the automated driving behavior models used for traffic simulation in addition to some of the prior/ongoing work on CAV-related traffic control and policies, such as speed harmonization and reserved lanes for automated vehicles. Early automated driving models focus on automating car-following as an assistant system to the driver. To do so, the models assume that vehicle uses basic sensors to get information about relative speed and distance to the leading vehicle. Using such information, the vehicle is able to adjust its speed automatically, keeping a safe distance from the leading vehicle. Such systems are called “advanced cruise control” or “adaptive cruise control.” Other models extended adaptive cruise control systems to include V2V and V2I communication technology in order to predict the traffic state ahead of the vehicle and create platoons that can travel at closer relative distances. Such systems are called “cooperative adaptive cruise control.” Table 7 provides a summary of selected studies on the impacts of automated cruise control systems on traffic flow. The studies are described further in the following subsections.

Table 10. Summary of selected studies on the impacts of AICC/ACC and CACC on traffic flow.

Study	Model	Connectivity	Major Findings
Ioannou and Chien (*17*)	AICC	No	AICC can lead to smoother traffic flows and larger traffic flow rates, and can outperform human driving in emergency cases
Van Arem et al. (*37*)	AICC	No	AICC can reduce the number of shockwaves generated in traffic stream and the number of vehicles inside them In high demand scenarios, AICC can deteriorate flow rate
James et al. (*41*)	ACC; different models	No	ACC has a minor impact on traffic flow at low market penetrations while it has a negative impact at higher market penetrations
Van Arem et al. (*42*)	CACC	Yes	Traffic flow improves at high demand and CACC market penetrations while it deteriorates at low market penetrations
Vander Werf et al. (*38*)	ACC/CACC	No/Yes	ACC systems have minimal effect on highway capacity even at high market penetrations while CACC systems have a significant effect on highway capacity that is proportional to the market penetration of the technology

Table 10. Summary of selected studies on the impacts of AICC/ACC and CACC on traffic flow. (continued)

Study	Model	Connectivity	Major Findings
Shladover et al. (*49*)	ACC/CACC	No/Yes	ACC is unlikely to produce a significant increase in capacity
Melson et al. (*66*)	CACC – Network Dynamic Traffic Assignment	Yes	Travel time reductions proportional to demand levels and significant reduction in congestion due to CACC

Source: FHWA 2018

ACC = Adaptive cruise control. AICC = automated intelligent cruise control. CACC = cooperative adaptive cruise control.

Automated Intelligent Cruise Control/ Adaptive Cruise Control

In one of the early works on automated driving models, Ioannou and Chien (*17*) developed an automated intelligent cruise control (AICC), also referred to as adaptive cruise control (ACC), system for automatic car-following where they examined the system's effect on traffic flow and compared its performance with human driver models. The AICC system does not exchange information with other vehicles, but has access to relative speed and velocity with respect to the leading vehicle. To eliminate oscillation effects, the authors used a safe distance separation tool that is proportional to the vehicle velocity (constant time headway), and designed the system accordingly. The constant headway was calculated using a worst-case stopping scenario.

The authors used simulation experiments to compare AICC with three human driver models. The oscillations and long settling times observed with human driver models are non-existent in automatic vehicle following. Results indicated that automatic car following can lead to smoother traffic flows and higher traffic flow rates due to automated vehicles driving with shorter safety spacing, and less reaction times. The authors also concluded that AICC could outperform human driving models in different emergency cases like emergency stopping and cut-ins. More information on the control logic and simulation experiments are found in the paper.

In another work on modeling AICC, Van Arem et al. (*37*) proposed a system that automatically maintains a desired speed of the vehicle taking into account a minimal headway with respect to the leading vehicle. As in the case of Ioannou and Chien's work (*17*), the system is assumed to be independent and disconnected from other vehicles or road-side systems. Furthermore, the driver is assumed to take over control of in case of emergencies. The authors used the simulation model MIXIC to study the potential impact of AICC on traffic. The model assumes that relative speed and distance is obtained from a basic sensor.

Simulation results showed that AICC could reduce the number of shockwaves generated in a traffic stream, and reduce the number of vehicles inside those shockwaves, indicating a more stable traffic flow. However, in some simulated scenarios where traffic demand was high, results showed that, under the particular assumptions made by the authors, AICC might lead to degraded traffic performance. On the other hand, low AICC penetration had no significant effect on traffic flow properties.

James et al. (*41*) assessed the impacts of ACC on traffic flow using four ACC car following models programmed into the simulation platform VISSIM. The ACC models tested were MIXIC (*47*), IIDM (*65*), Path empirical (*50*), and Delft empirical (*39*). Furthermore, the models were calibrated using data collected with a 2013 Cadillac SRX with a production ACC-enabled system while following a human-driven 2013 Cadillac SRX in northern Virginia. The results show that the models tested are different in their sensitivity to calibrated coefficients. In addition, the simulations show that ACC has a minor impact on traffic flow at low market penetrations while it has a negative impact at higher market penetrations emphasizing the importance of connectivity in automated cruise systems.

Cooperative Adaptive Cruise Control

Van Arem et al. (*42*) extended the concept of AICC to include V2V communications so that automated vehicles can follow leading vehicles at a closer distance. In addition to knowing relative distance and speed, V2V communications allows vehicles to coordinate speed changes, exchange precise speed information, accelerations, warning of forward and hazards, and maximum braking capabilities. The authors used the traffic simulation tool MIXIC to study the cooperative adaptive cruise control (CACC) effect on traffic characteristics.

Simulation results showed an improvement in traffic-flow stability and a slight increase in traffic-flow efficiency. The traffic flow especially improves in conditions with high-traffic volume and when high fractions of the vehicle fleet are CACC equipped. At low-CACC presence (< 40 percent), results indicted a degradation of performance demonstrated by lower speeds, higher speed variances, and more shock waves. The system has a negative effect on traffic safety in the merging process; close CACC platoons prevent other vehicles from cutting in resulting in an increasing number of removed vehicles due to conflicts. As for shockwave, simulations showed a decrease in the number of shockwaves before a lane drop when a high number of CACC-equipped vehicles are present.

In another work by Vander Werf et al. (*38*), the authors studied the effects of Adaptive Cruise Control (ACC) and CACC on highway traffic flow capacity using a Monte Carlo simulation approach. Three types of vehicles were simulated in the study: 1) vehicles driven by humans, 2) vehicles equipped with ACC system to control speed with 1.4 s time gap, and 3) vehicles equipped with CACC system enabled by V2V and using a time gap of 0.5 seconds. Furthermore, the two automated cruise systems were simulated for different scenarios by varying market penetrations.

The study results show that ACC systems have minimal effect on highway capacity even at high market penetrations (7 percent increase in capacity at most.) On the other hand, CACC have a significant effect on highway capacity that is proportional to the market penetration of the technology. At full CACC market penetration, for example, the highway capacity can increase to more than double the capacity of the base case (without ACC or CACC systems)

Shladover et al. (*49*), also studied the effect of Adaptive Cruise Control - ACC and CACC on highway capacity using the micro-simulation tool AIMSUN. The authors used the distribution of time gap settings by drivers that participated in real field experiments prior to the study. The authors simulated four types of vehicles: manual vehicle with driving behavior represented by the NGSIM oversaturated flow model, ACC vehicle with driving behavior represented by a simple first-order control model, Here-I-am (HIM) vehicle which constantly broadcasts its location, and CACC vehicle that uses its capability if it follows HIA or CACC vehicle and acts as a normal ACC vehicle otherwise.

Results showed that ACC is unlikely to produce a significant increase in capacity as drivers are comfortable with driving gaps that are similar to the gaps drivers choose when driving manually. CACC, however, showed a potential for significant increase in capacity at high market penetration. This is due to drivers being more confident in following vehicles with shorter gaps due to higher dynamic response of CACC over ACC.

In addition to the abovementioned microsimulation approaches, Melson et al. (*66*) studied the effect of CACC at the network level by incorporating CACC into the link transmission model (LTM) for dynamic network loading. As a first step, the authors derived the CACC flow-density relationship (fundamental diagram) of CACC from the MIXIC car following model. After verifying the fundamental diagram with the observed speeds and flows using the simulation platform VISSIM, the authors created a network loading model using the aforementioned fundamental diagram in LTM.

Comparing DTA and MIXIC microsimulation on a subnetwork, both models predicted travel time reductions (up to 32 percent) with increasing demand as a result of CACC. The authors also tested CACC on two larger networks: a 28-mile corridor of I-35 near Austin, Texas where all vehicles were assumed to be equipped with CACC, and the Round Rock Network where one CACC lane was added. Results of both networks show a significant reduction in congestion due to CACC, however, the Round Rock network results indicate an increase in the overall travel time due to rerouting. This underscores the importance of including user route choice in the DTA analysis of CACC.

Information Routing Protocols and Communication Networks

Information routing protocols in the literature can be categorized into two distinct groups: topology-based (ad-hoc) protocols and position-based protocols. Ad-hoc routing methods have been originally developed for mobile ad-hoc networks (MANETs), which share certain similarities with vehicular ad-hoc networks (VANETs), including self-organization and low transmission range. Therefore, some of MANET specific routing protocols can be used in VANETs (*86*). AODV (ad-hoc on-demand distance vector) (*87*) and DSR (*88*) are among the routing protocols originally developed for MANETs that can also be used in VANETs. VANETs, however, are more dynamic, and using MANET-specific routing protocols can result in poor routing performance and low throughput (*89*). Note that MANET specific routing protocols are the only routing protocols available in ns-3.

Cluster-based routing protocols are another category of position-based protocols. A cluster consists of a cluster head and several cluster members. Cluster members can only communicate with their cluster head and cluster heads can communicate with their cluster members and other cluster heads. Various criteria have been proposed to form the clusters and select the cluster head, such as respective locations, speed difference (*48*), link quality, node position, and node reputation (*90*). Bhaumik et al. (*91*) proposed a clustering routing protocol based on the affinity propagation clustering algorithm (*92*), in which each node calculates its similarity to other neighbors and connects to the most similar node. Stable clusters are the key to effective information routing through clusters and to avoid unnecessary signal interference.

The Node Mobility Model (ns-3) provides several native mobility models. However, similar to routing protocols, these mobility models are MANET specific and do not address the VANET mobility needs. Therefore, several efforts have been made in the literature to incorporate vehicular movements into different wireless communication simulators. Harri et al. (*93*) present a comprehensive review of these efforts. However, as mentioned previously, these mobility models are not sensitive to the flow of information in a connected environment.

Integrated Traffic-Telecommunication Framework for Simulating connected and Automated Vehicles - Northwestern University Transportation Center

To explore questions regarding the flow impacts of connected and/or automated vehicles, it is important to formulate microscopic models that capture the capabilities of the new technologies as well as the attendant behavior of human drivers. For human drivers, one could rely on a variety of existing models, albeit actual behavior will only be observed when there is sufficient deployment of these technologies. Specific logic for autonomous vehicles will be robotic in nature and essentially supplied by the operating entity, and thus likely proprietary. Connected vehicle behavior would be largely dependent on the implemented capabilities. One of the first efforts to model the interactions between different driving behaviors in connected environment is the simulation platform developed by Talebpour et al. (*94*) at the Northwestern University Transportation Center (NUTC).

The abovementioned platform integrates three different driving behaviors: regular vehicles, connected vehicles, and automated vehicles. For regular vehicles, the authors relied on a stochastic car-following model introduced by Hamdar et al. (*95*) and extended by Talebpour et al. (*96*). The model, which is based on the Prospect Theory (*97*), captures drivers' crash-avoiding behavior while maintaining a desired speed. For modeling connected vehicles, the authors opted for a deterministic Intelligent Driver Model (IDM). The authors choice of a deterministic model is based on the assumption that connected drivers are more certain about other drivers' behaviors, since they exchange information in real time through V2V and V2I communications. Finally, for modeling automated vehicles, Talebpour et al. (*98*) introduced a car-following model for automated vehicles based on the previous simulation studies by Van Arem et al. (*42*) and Reece and Shafer (*99*). In their model of automated vehicles, the authors considered two main factors: (1) their ability to constantly monitor other vehicles in their vicinity, which can result in a deterministic behavior in dealing with other drivers' behavior; and (2) their ability to react almost instantaneously to any changes in the driving environment.

With respect to modeling wireless telecommunications, the Node Mobility Model (ns-3) was integrated with the microscopic vehicular traffic simulation framework described in this section. Thus, the positions of the vehicles are governed by the micro rules in the simulator, including whatever messages may be received through the VANET, as transmitted by ns-3 to the vehicles in their evolving positions.

The integrated platform was used to test the traffic throughput and stability impacts of mixed traffic streams with varying compositions of automated and/or connected vehicles (*25*). The throughput analysis shows that higher market penetration of CAVs results in a higher throughput and that automated vehicles have a higher impact on throughput than connected vehicles. Similarly, the stability analysis shows that string stability increases at higher CAV market penetration and that automated vehicles also have a higher impact on stability than connected vehicles.

Control-related Applications in a Connected and Automated Vehicle Environment

Speed Harmonization in a Connected Vehicle Environment

Speed harmonization is a form of variable speed limit control that adjusts and coordinates the maximum appropriate speed limit on the basis of the prevailing traffic conditions, as way of avoiding or mitigating shock wave formation, dampening its propagation, and minimizing incident-related hazards by controlling vehicular speeds and reducing the spatial variance of traffic speeds (*10; 26; 76; 84; 100*). It is generally coupled with sensing aimed at early shock wave detection to avoid and mitigate flow breakdown (*10*). Conventional installations of speed harmonization rely on fixed sensors to monitor traffic, and accordingly display the same dynamic speed limits at fixed location installations (overhead mounts).

Connected vehicle technology allows sensing anywhere there are connected vehicles, which effectively act as probes, considerably extending the spatial realm over which shock waves might be detected, ensuring earlier detection with appropriate algorithms (*76*). Similarly, speed limits could be displayed to drivers in connected vehicles individually, allowing greater range for the effectiveness of the strategy, in addition to enabling a finer gradation of displayed speeds, e.g. based on upstream distance from the projected tail of the shock wave.

Automated vehicle technology, on the other hand, can also help dampening shockwaves through controlling velocity of automated vehicles in the traffic flow (*44*). In a field experiment conducted by Stern et al. (*44*) on a closed ring road, the authors found that one automated vehicle can control the flow of at least 20 human controlled vehicles around it. The speed-controlled automated vehicle can substantially reduce the speed variation among vehicles, excessive braking, and fuel consumption.

In Ma et al's review (77) of recent speed harmonization algorithm developments, summarized in Table 8, the authors categorized the CAV-enabled algorithms into: 1) algorithms that use shared information with CV system (79; 81-83) and 2) algorithms that control vehicles equipped with CAV systems (84; 85). The results of the studies reviewed show the effectiveness of CAV-enabled speed harmonization in delaying and/or dampening traffic oscillations, in addition to improving safety and sustainability.

Table 11. Summary of recent studies on speed harmonization applications enabled by connected and automated vehicle systems

Study	Comm.	Input	Control Algorithm	Results
Lu et al. (*75*)	V2I	Segment speeds, detailed trajectory-level data not necessary	Reduce speed limits of freeway segments upstream of a bottleneck in proportion to the observed bottleneck speed if vehicle flow throughputs are above the bottleneck capacity	Works for a corridor and a freeway network with multiple bottlenecks

Table 11. Summary of recent studies on speed harmonization applications enabled by connected and automated vehicle systems. (continued)

Study	Comm.	Input	Control Algorithm	Results
Talebpour et al. (*76*)	V2I	Detailed microscopic vehicle trajectory	A wavelet-transform based algorithm to detect formation of perturbations; a cognitive risk-based microscopic simulation model was adopted to account for human behavior; a reactive speed limit was selected to implement SH reactive speed limit was selected to implement SH	Effectively delay or eliminate traffic breakdown and improve traffic safety even at a low penetration rate of 10%
INFLO project (*77*)	V2V/V2I	Speed measured from connected vehicles and infrastructure-based sensors	Group freeway sub-links with similar recommended speeds to produce harmonized speeds	SH effectiveness depends upon driver compliance
Li et al. (*45*)	V2V	Leading vehicle's input	CAV car-following rule	Effectively suppress development of oscillation and consequently mitigate fuel consumption and emission
Wang et al. (*101*)	V2I	Aggregated traffic state	Use aggregated traffic state information to detect formation of congestion at a bottleneck; each CAV processes the VSL signals from the central control unit individually	The connected VSL and vehicle control system improves traffic efficiency and sustainability, i.e., total time spent in the network and average fuel consumption rate are reduced
Yang and Jin (*78*)	V2I	Individual vehicle's information	Advisory speed limit is calculated by each individual vehicle and then averaged among green driving vehicles	When 5% of the vehicles implement the green driving strategy and the communication delay is 60 s, the fuel consumption can be reduced by up to 15%

Table 11. Summary of recent studies on speed harmonization applications enabled by connected and automated vehicle systems. (continued)

Study	Comm.	Input	Control Algorithm	Results
Ahn et al. (*102*)	Radar and V2V	Topographic information, the spacing between the subject and lead vehicle, and a desired (or target) vehicle speed and distance headway	Use a rolling horizon-based optimization approach to control vehicle speed within a preset speed window in a fuel-saving manner	Simulated fuel savings in the range of 27% are achieved with an average vehicle spacing of 47 m along a study section of Interstate 81

Source: Ma, J., X. Li, S. Shladover, H. A. Rakha, X.-Y. Lu, R. Jagannathan, and D. J. Dailey. 2016. Freeway speed harmonization. *IEEE Transactions on Intelligent Vehicles*, 1(1): 78-89.

Dedicated Lanes for Automated Vehicles

One approach to attain greater throughput gains in mixed traffic situations could be to provide dedicated lanes for auomated vehicles. Such lanes can minimize the interactions between regular and automated vehicles and provide the opportunity to significantly increase the density of automated vehicles in those lanes. While adding dedicated lanes to the current roadway system is an expensive approach, a more feasible approach is to prevent regular vehicles from using one or more lanes and reserve those for autonomous vehicles on existing multilane facilities. Such an approach, however, may significantly increase congestion and reduce throughput in the regular lanes.

Similar approaches have been widely implemented in transportation systems to deal with the growing demand for travel and to reduce congestion. Managed lanes, high occupancy toll (HOT) lanes, high occupancy vehicle (HOV) lanes, and express lanes are all based on a similar concept. A key element in all these approaches is designing effective strategies and/or pricing schemes to attract enough travelers to those lanes to reduce the congestion in the main lanes, while keeping the flow within the managed/HOT/HOV/express lanes at pre-breakdown levels (*104*). Despite the similarities between the concept of reserved lanes for autonomous vehicles and those congestion management approaches, designing reserved lanes in this case faces additional complexities arising from the interactions between regular and autonomous vehicles.

To address these challenges and to explore the potential effects of reserving a lane for autonomous vehicles, Talebpour, Mahmassani and Elfar (*105*) applied the microscopic simulation platform described in Section 0 to a 3.5-mile section of a four-lane freeway in the Chicago region. Three distinct operational policies are tested in conjunction with reserving the leftmost lane for autonomous vehicles: (1) mandatory use of the reserved lane by automated vehicles, (2) optional use of the reserved lane by automated vehicles, and (3) limiting the automated vehicles to operate autonomously in the reserved lane.

The findings of these investigations suggest that the optional use of the reserved lane without any limitation on the type of operation can improve congestion and reduce scatter in the fundamental diagram. In contrast, limiting autonomous vehicles to the reserved lane and preventing autonomous operation in regular lanes could significantly increase congestion and result in breakdown formation. In particular, mandatory lane-changing maneuvers of automated vehicles are the main source of shockwave formation. The analysis is extended to higher overall flow levels (beyond those currently observed on that facility) to explore the minimum and optimal threshold levels for introducing such reserved lanes. In this case, reserving one of the four lanes for automated vehicles is only beneficial at market shares above 30 percent. Furthermore, travel time reliability analysis revealed that optional use of the reserved lane can yield the most benefit

In a working paper by Su et al. (*106*), the authors investigated introducing CACC vehicles using three lane management strategies. The first strategy is HOV-only where the left-most lane accepts only HOV vehicles. In the second strategy, the left-most lane is open to both HOV and CACC vehicles. In the third one, the managed lane is only open to CACC vehicles. The three scenarios were simulated using a microscopic freeway simulation platform VISSIM and the MIXIC model for dynamic CACC operations in a 14-mile section of Interstate-66 near Washington, DC.

The simulation results showed that the dedicated CACC lane's capacity can reach as high as 3800 vphl because of having higher and more stable speeds than general purpose lanes. However, for low market penetrations, the analysis shows that dedicated lanes are inefficient. For market penetration (MPR) below 25 percent, HOV + CACC is the best strategy where capacity increases by 10 percent for 25 percent MPR over the base case. At 45 percent MPR, the CACC only strategy was the best out of the three where capacity increased by 10 percent for the whole corridor.

Intersection Control with Connected and Automated Vehicles

Flow control at urban intersections with connected and automated vehicles is critical to the overall performance of the transportation system. If increases in throughput on major freeways and arteries are met with limited capacity and sluggish performance on urban streets and junctions, queues and gridlock will result. Unfortunately, the opportunities at intersections are more difficult to realize, largely because, by their very function, junctions require the allocation of limited capacity to conflicting movements. Unless all parts of a conflict can communicate, the lowest common denominator will prevail, meaning the characteristics of regular unconnected vehicles will play the predominant role in overall performance.

Development in automated vehicle logic for maneuvering at and around signalized intersections in urban areas has focused primarily on ensuring safety, especially with regard to the wide array of entities typically present in the urbanscape, such as pedestrians, bicycles, skateboards, and other shapes not typically present in a freeway environment. Hence it is natural that risk aversion would take precedence over performance in developments to date. As the artificial intelligence and pattern recognition algorithms operating on multiple vehicle-based sensors continue to mature, one can expect shorter reaction times as the light turns from red to green, and snappier discharge rates from queues (shorter headways), which would increase the nominal approach capacities, resulting in lower overall delay. However, to the extent that the discharge from a queue can be held up by a long-headway vehicle, these benefits will remain relatively minor, especially at low market shares.

Communication is the key to improving intersection performance. Hence much development to date has targeted connected vehicle environments, and in the limit automated vehicles in connected environments. Three types of strategies have been suggested, in increasing order of market penetration required.

1. Using data from connected vehicles to improve adaptive signal control operation.

This is the proverbial "low-hanging fruit" under low market penetration rates of connected vehicles.

Connected vehicles essentially act as vehicle probes that provide information on the prevailing traffic system, that the (signal) controller could use as a basis for more or less predictive control. In its least ambitious form, connected vehicles augment existing fixed sensors to provide more complete information to existing control logic. More sophisticated strategies devise more powerful data-driven control logic with varying projection horizons and spatial scope. The main improvement due to these strategies arises from enabling more responsive traffic signal control. As such, it is bounded by the improvement that one could expect from better signal control, which is typically limited in congested urban contexts (*73*). Examples in this general category include work by Priemer and Friedrich (*67*), Goodall et al. (*72*) and Feng et al. (*107*).

2. Improving service rates through opportunistic coordinated platooning.

The main idea in these approaches is to combine whenever possible connected vehicles on a particular approach that wish to traverse an intersection, and serve them in a coordinated platoon, thereby improving the saturation flow rates for those cycles where there is sufficient presence of platoonable vehicles. Lioris et al. (*40*) have conducted simulation experiments to evaluate the strategy under simplifying assumptions, for different market penetrations of connected vehicles. Related approaches for opportunistic signal operation in the presence of connected vehicles are discussed in Guler et al. (*71*).

3. Eliminating signals altogether through individual trajectory coordination in 100 percent connected environment, preferably with automated vehicles.

This approach has received the most hype in the popular media, featuring automated vehicles in fully connected environments seamlessly negotiating their way through busy intersections without the need to stop. Algorithms have been proposed and tested through simulation in a few instances by Hausknecht et al. (*69*) Fajardo et al. (*74*), and Lee and Park (*68*). A major unknown in the proposed approaches is the extent to which they may scale up, to typical congested urban intersection levels, and to operation at more than just one or a few isolated intersections, to encompass an entire network. In addition, safe and reliable schemes to accommodate pedestrians and bicycles (where applicable) remain to be demonstrated. These are important questions for further research as interest in deploying the infrastructure for such connected systems continues to gain ground as part of the smart cities narrative.

Chapter 5. Identified Data Sources for Connected and Automated Vehicle Analysis, Modeling, and Simulation in Prior/Current Work

This chapter identifies existing data sources as well as emerging ones which are required to support the AMS capabilities for connected and automated vehicles at the strategic and operational levels. An assessment of the identified sources is discussed in detail in the Task 5 report (*5*)

Data Sources for Supply-related Connected and Automated Vehicle Analysis, Modeling, and Simulation

The review of work on the supply-related impacts of CAVs focused on the operation of Shared-Automated-Vehicles as a new mobility option that is enabled by CAV technology. The review showed that researchers have already started formulating different scenarios in which new mobility modes are operating and building different tools to model the SAV operation. Table 12 summarizes the data used in the selected studies.

Some researchers approached SAV modeling as a special case of fleet management problems (*59*) and defined it as a dynamic, multi-vehicle pickup and delivery problem with explicit or implicit time-window constraints to inform future research on automated vehicle fleets. Other groups proposed frameworks for modeling SAV (*60; 61*) such as an event-based simulation with two main events: 1) a demand simulator and 2) an SAV dispatcher. Other studies developed agent-based simulation tools to evaluate the impacts of the new shared mode (*54; 56*). Below is a description of the main data sources identified.

Table 12. Summary of reviewed papers which are related to SAV modeling.

Study	Model	Data
Levin et al. (*60*)	Event-based framework for modeling SAV vehicles where the first event introduces demand and the second event dispatch SAVs to fulfil that demand	• Subnetwork of Austin, Texas. Consists of downtown grid with freeway and arterial corridors. It has 171 zones, 546 intersections, 1,247 links, and 62,836 trips over 2 hours in the AM peak
Fagnant and Kockelman (*56*)	Agent-based simulation	• Network of Austin, Texas available through The Capital Area Metropolitan Planning Organization's (CAMPO). It is comprised of 13,594 nodes and 32,272 links (including connectors). • Trip data from the 2009 NHTS Data for Texas
Chen et al. (*54*)	Agent-based simulation for Shared-Automated-Electrical Vehicles (SAEV)	• Hypothetical gridded city, 100-mile 146 by 100-mile gridded metropolitan area • Trip data from the 2009 NHTS Data for Texas
Mendes et al. (*61*)	Event-based simulation comparing SAV to light rail	• Proposed light rail line connecting Brooklyn and Queens in New York City

Source: FHWA 2018

Basic Roadway Infrastructure Physical Characteristics

Basic characteristics of the infrastructure are required to model the operation of SAVs over the network. These can include real networks, such as the Austin, Texas subnetwork used to model SAV in Levin et al's study (*60*), or hypothetical ones such as the gridded network created by Chen et al. (5) for their study of electric SAVs.

Baseline Aggregate Traffic Conditions

Aggregate traffic data, such as traffic volumes, speeds, and densities, are used to calibrate the traffic models and network models used in simulating SAV operations. For example, Levin et al. (*60*) used traffic data from the Capital Area Metropolitan Planning Organization to calibrate the network models in the SAV operation framework of Austin, Texas.

Travel Demand Data

In the context of modeling SAVs travel demand data is used to define the number of trips/individuals that needs to be served by an SAV fleet on a network. Fagnant and Kockelman (*56*), for example, used the 2009 National Household Travel Survey (NHTS) data of Texas to set the demand for their numerical experiments and determine the optimal fleet size required to serve that demand. Chen et al. (5) also used the demand of 2009 NHTS data for Austin, Texas to define the number of trips on a hypothetical gridded network modeled after Austin, and determine the optimal electric SAV fleet size to serve the number of trips based on vehicle range, battery recharge time, and charging station locations. Mendez et al. used 2035 origin-destination projections by the New York City

Department of Transportation to compare an SAV system to light rail line between Brooklyn and Queens in New York.

The NHTS data set is one particular source that has been used by multiple studies on SAV operations to set or calibrate the number of trips on networks. The survey collects information on daily trips which mainly include the purpose, mode, trip duration, time of day, day of the week, and vehicle occupancy (for private vehicles).

Performance Characteristics of Connected and Automated Vehicle Systems

Performance characteristics of automated vehicles are often assumed by researchers or in some cases are based on limited field experiments to model the operations of SAV fleet. Those assumptions, in the case of SAV modeling, include among others vehicle capacity, connectivity, and travel range.

Data Sources for Demand-related Connected and Automated Vehicle Analysis, Modeling, and Simulation

The review of work on the demand-related impacts of CAVs addressed the potential changes the technology could bring to the travel demand and behavior. The review covered four main impacts/changes: 1) adoption of CAV technology, 2) travel mode shifts, 3) vehicle ownership, and 4) vehicle miles traveled (VMT) changes.

Previous research predicted the adoption rate of the new technology and the characteristics of users who are likely to use it using different approaches. Some studies compared the deployment of CAV systems to previous new technology deployments such as automatic transmission (*27*) and Hybrid Electric Vehicles (*28*), or used network level simulations (*81*). Other studies conducted stated preference surveys to characterize adopters of the new technology (*35; 82*).

Table 13 provides a summary of the data sets used in predicting the adoption rate of CAVs.

Table 13. Summary of selected studies on connected and automated vehicle technology adoption.

Study	Model	Data
Litman (*27*)	Comparison to previous vehicle technology deployment	• Historical data for previous technology deployment
Lavasani (*28*)	Generalized Bass diffusion models	• Historical sales of Hybrid Electric Vehicles in the US • Internet and cellphone adoption from the World Bank database • Demographic data

Table 13. Summary of selected studies on connected and automated vehicle technology adoption. (continued)

Study	Model	Data
Bansal and Kockelman (*81*)	Agent-based simulation	• U.S. survey of 2167 participants regarding their preferences for CAV technology and their household annual vehicle transactions
Lavieri et al. (*82*)	Generalized Heterogeneous Data Model; Structural equations	• Puget Sound Regional Travel Survey, 2014-2015, collected for 1,832 individuals; includes detailed information about socio-economic, demographic, activity-travel characteristics, attitudes and preferences including those towards AV technology
Haboucha et al. (*35*)	Logit Kernel choice model of autonomous vehicles	• Stated preference survey on AVs; September-November 2014 in the US and Israel; 721 individuals; questions included driving habits,

Source: FHWA 2018

In terms of potential mode shifts caused by CAV systems, the literature approached the question by modifying existing demand models and adding the AV vehicles as a new mode (*34; 36; 83*). The characteristics of the new vehicles like costs and value of time were derived from finding of and predictions of other studies in addition to performing sensitivity analysis to different assumed values.

Table 14 provides a summary of the data sets used by selected studies on potential mode shifts caused by CAV systems.

Table 14 Summary of selected studies on mode shift due to the introduction connected and automated vehicle technology.

Study	Model	Data
Childress et al. (*83*)	Seattle region's activity-based model	• AV mode characteristics are based on findings of previous studies
LaMonida et al. (*34*)	Trip generation and choice models	• Michigan State's 2009 Long-Distance Travel Survey
Perrine et al. (*36*)	Modified travel demand model, rJourney	• Journey long-distance trips traveled throughout the united states in 2010; 1.17 billion rJourney tours are generated from a synthesized household population of 31.5 million; four travel modes including automobile, bus, rail, and airlines

Source: FHWA 2018

As for CAV impacts on vehicle ownership, former studies, tried to evaluate those impacts by directly asking travelers in the form of stated preference surveys (*55*) or by developing simulation platforms with SAV service (*53; 54*). Table 15 provides a summary of the data sets used by selected studies on the abovementioned impacts.

Table 15. Summary of selected studies on connected and automated vehicle impacts on vehicle ownership.

Study	Model	Data
Schoettle and Sivak (*52*)	Descriptive analysis	• Trip data from the 2009 NHTS
Fagnant and Kockelman (*53*)	Agent-based simulation	• Hypothetical gridded network; 10 mi x 10 mi • Trip rates from the 2009 NHTS data
Chen et al. (*54*)	Agent-based simulation, Electric SAV	• Hypothetical gridded city, 100-mile 146 by 100-mile gridded metropolitan area • Trip data from the 2009 NHTS Data for Texas
Zmud et al. (*55*)	Descriptive analysis	• Online survey of 556 residents of the Austin metropolitan area on consumer acceptance of AVs • Face-to-face interviews with 44 people

Source: FHWA 2018

Finally, previous studies in the literature evaluated the impacts of AVs on VMT by modifying existing activity-based models (*83; 85*), four-step models (*33*), or through agent based simulation (*54*). Some studies studied the impacts qualitatively by relating the new technology to other technology deployments (*27*) or through stated preference surveys (*55*). Table 16 provides a summary of the data sets used by selected studies on the potential VMT impacts caused by CAVs. The identified data sources are discussed further next.

Table 16. Summary of selected studies on the impacts of isolated-automated vehicles on vehicle miles traveled.

Study	Model	Data/Testing
Litman (*27*)	Comparison to previous vehicle technology deployment	• Historical data for previous technology deployment
Childress et al. (*83*)	Seattle region's activity based model	• AV mode characteristics are based on findings of previous studies
Kim et al. (*85*)	Modified Atlanta regional activity based model	• AV mode characteristics are based on findings of previous studies
Auld et al. (*32*)	Modified POLARIS activity based model	• Chicago, Illinois network; 31,278 links and 18,951 nodes; bus and rail lines and stations; 3.8 million households; 27.9 million trips on an average day
Zhao and Kockelman (*33*)	Modified four-step model	• Existing model for Austin, Texas
Chen et al. (*54*)	Agent-based simulation, Electric SAV	• Hypothetical gridded city, 100-mile 146 by 100-mile gridded metropolitan area • Trip data from the 2009 NHTS Data for Texas

Table 16. Summary of selected studies on the impacts of isolated-automated vehicles on vehicle miles traveled. (continued)

Study	Model	Data/Testing
Zmud et al. (*55*)	Descriptive analysis	• Online survey of 556 residents of the Austin metropolitan area on consumer acceptance of AVs • Face-to-face interviews with 44 people

Source: FHWA 2018

Historical sales data of other vehicle technologies

Historical sales data of other vehicle technologies, such as automatic transmission and airbags, was used by some studies (*27; 28*) to predict the pattern of CAV technology deployment in the future. Lavasani (*28*), for example, used historical data of hybrid electric vehicles in the U.S. in addition to demographic data to predict the sales of AVs in the future.

Socio-demographics and Economics Data

Socio-demographic and economic data are used extensively in evaluating the demand impacts of CAV systems. The data can be either obtained from national data sets, such as the US Census (*28*), or are asked for directly in travel surveys (*81; 82*). Lavasani (*28*), for instance, used socio-demographic data to characterize the early adopters of CAV systems such as age, education, and wealth.

Consumer Decisions about Purchase and Use of Connected and Automated Vehicle Systems

As an emerging technology, limited information is available on the actual purchases or consumer perception of CAV technology. Therefore, consumer surveys about their opinion of the new technology and potential behavioral changes are one way to obtain such information. Bansal and Kockelman (*81*), for example, surveyed 2167 Americans about their willingness to pay for the new technology and their annual vehicle transactions, among other factors, to calibrate an agent-based simulation model and predict the long-term adoption of the CAV systems. The Puget Sound Regional Travel study is another example of consumer perception surveys (10). The same data collection approach was used in other papers to predict the characteristics of early adopters (10) and impacts on vehicle ownership (*55*).

This is an example where revealed preferences are difficult to observe because the new technologies have not been deployed yet, and are not available to the general public. Thus stated preference surveys and stated choice experiments are the main approach that has been used in previous studies. However, developments in technology are enabling more sophisticated approaches to engage respondents and obtain information that is believed to be more reliable. These approaches entail use of virtual reality and interactivity to make the stimuli (state choice questions) as relevant as possible to both the respondent and the objectives of the study.

Travel Demand Data

Traditional travel surveys were used in some papers as a basis for modifying mode choice models and including automated vehicles as a new option. The 2010 Michigan statewide model long-distance trip forecasts, for instance, was used by LaMonida et al. (*34*) to build trip generation and modal choice models where AV were introduced as a new mode with lower perceived travel time costs. As another example, the long-distance trip tours of the national long-distance travel model, rJourney, were used by Perrine et al. (*36*) to extend the model and add the automated vehicle option. The 2009 National Household Travel Survey (NHTS) was analyzed by Schoettle and Sivak (*52*) to explore theoretically to what extend SAV can reduce household vehicle ownership.

Likewise, as discussed in connection with the preceding item, stated choice experiments have played an increasingly significant role in eliciting preferences and likely behaviors under different scenarios that may not yet have a real-world analogue.

Basic Roadway Infrastructure Physical Characteristics

The basic configuration of network and road infrastructure is required as input for agent-based simulation models to evaluate the demand related impacts of CAV systems such as travel time and VMT. It might also be required to estimate travel time for other demand models such as the four-step. The network configuration can be hypothetical or based on a real network. For example, a hypothetical gridded network was used by Fagnant and Kockelman (*53*) in their agent-based simulation to evaluate the impacts of CAVs on vehicle ownership. Chen et al. (*54*) also used a hypothetical network configuration in an agent-based simulation model to evaluate the impacts of electric SAV fleets on vehicle ownership.

Data to Support Activity-based Demand Models

Some existing activity-based models were modified to include CAVs as new modes and evaluate their demand-related changes. For instance, an activity-based model for the Seattle region was modified by Childress et al. (*83*) to add AV as a new mode to evaluate the impacts of it on VMT. Kim et al. (*85*) and Auld et al. (*32*) followed a similar approach by modifying activity-based models for the Atlanta metropolitan region and Chicago city in Illinois, respectively. To date, no CAV-specific data has been obtained to reformulate or recalibrate these models; rather modifications have consisted in expanding the choice set of alternatives while keeping the same basic weights on various attributes.

Data Sources for Operation-related Connected and Automated Vehicle Analysis, Modeling, and Simulation

The review of work on the operation-related impacts included efforts of modeling AVs which focused on modeling automated cruise control, such as ACC and CACC systems (*17; 37; 38; 41; 42; 49; 66*), in addition to modeling mixed traffic conditions (*25*). Below is a description of the data sources used in those studies. Table 17 provides a summary of the data used in selected studies.

Table 17. Summary of selected studies on the impacts of Automated intelligent cruise control (AICC)/ adaptive cruise control (ACC) and Cooperative adaptive cruise control (CACC) on traffic flow.

Study	Model	Data
Van Arem et al. (*37*)	AICC	• Traffic data collected on the A2 between Utrecht and Amsterdam, Netherlands; consists of arrival instant, lane, speed and length of passing vehicles at 3 cross-sections • Hypothetical road network of a sequence of homogenous links without on or off ramps
James et al. (*41*)	ACC; different models	• Vehicle movement data collected on the Dulles Access Road in Northern Virginia by two 2013 Cadillac SRXs equipped with ACC system; includes accurate distance gaps, vehicle speeds, and vehicle accelerations at a frequency of 10 Hz • Hypothetical road networks; four-lane freeway facility with no disruption and three-lane facility with various bottleneck conditions
Van Arem et al. (*42*)	CACC	• Traffic data from the A4 highway, near Schiphol in The Netherlands; high volumes to simulate congestion
Vander Werf et al. (*38*)	ACC/CACC	• Traffic data from I-880 in the San Francisco Bay Area • Highway layout consisted of a single protected highway lane, with a ramp–highway junction consisting of a single-lane off-ramp followed immediately by a single-lane on-ramp
Shladover et al. (*49*)	ACC/CACC	• NGSIM vehicle trajectory data to calibrate manual driving • Vehicle movement data from a field study using two Nissan Infinity FX45s equipped with ACC/CACC systems
Melson et al. (*66*)	CACC – Network Dynamic Traffic Assignment	• Traffic data for Austin from the Capital Area Metropolitan • Planning Organization • Roadway configuration of I-35 corridor in Austin, Texas; 220 nodes, 95 zones, and 315 links • Network configuration of Round Rock; 2744 nodes (716 zones) and 4236 links
Talebpour et al. (*25*)	CACC	• NGSIM vehicle trajectory data • Freeway segment configuration for I-290 in Chicago, IL

Source: FHWA 2018

Basic Roadway Infrastructure Physical Characteristics

A basic configuration of the roadway infrastructure is required to define the study segments, links, or network over which the CAV systems is simulated. Similar to the demand and supply aspects of CAV AMS, the infrastructure configuration can be modeled after actual networks as in the case of

Talebpour et al’s (*25*) study where the authors modeled a segment of interstate I-290 in Chicago, Illinois or a hypothetical one as in the case of many other studies (*17; 49*).

Baseline Aggregate Traffic Conditions

Aggregate traffic conditions are required to calibrate/validate the various macroscopic and network traffic models (estimate their different parameters) to simulate actual traffic behavior and demand patterns. Those include aggregate measures of speed, density, and flows. For example, traffic data for the Austin I-35 corridor was used to calibrate the network simulations done by Melson et al. (*66*).

Performance Characteristics of Connected and Automated Vehicle Systems

The performance characteristics of CAV systems, such as time gaps, acceleration, sensor ranges, are key to evaluating the operation related impacts of those systems on the whole transportation network. For example, the sensor ranges can limit the safe speed at which automated vehicles can operate and hence the overall system flow (*25*). Due to the limited data on the actual behavior of CAV systems, their potential characteristics were assumed in most studies where sensitivity analyses were conducted using multiple scenarios (*17; 37; 38; 42*). Some studies assumed the CAV characteristics in the models using commercial ACC/CACC systems. For example, James et al. (*41*) calibrated the ACC models in their study using data collected by two 2013 Cadillac SRX vehicles with ACC systems operating under various acceleration/deceleration scenarios. However, due to the high efforts and expenses for collecting such data, the use of it is generally limited.

Operations of Traffic Control Devices and Management Strategies

Traditional traffic control information and strategies and algorithms can be integrated with CAV technology to design improved control systems that take advantage of connectivity and automation. For example, a traditional variable speed limit algorithm was integrated with connected vehicle technology to design an improved speed harmonization algorithm that can send speed limit messages directly to vehicles at the onset of shockwave formation (*76*).

Vehicle Trajectories

Vehicle trajectories provide the most complete information about the vehicles’ microscopic behavior such as speed, lane change, acceleration/deceleration which can be used to derive the macroscopic system behavior. In the case of CAV systems, vehicle trajectories are one of the key sources to validate and calibrate microscopic car following model for CAVs. This is because that some aspects related to the behavior of CAV technology can only be observed on the individual level, such as lane changes, time gaps, smooth acceleration.

The traditional 2D vehicle trajectories can also be extended to 3D trajectories whereas CAV impacts can be evaluated on the network level. Such as route choice and response to information. As an example for using vehicle trajectory to validate car-following models, Talebpour et al. (*94*) used vehicle trajectories collected through the Next Generation Simulation (NGSIM) program to calibrate the car-following models in simulation platform introduced to model mixed traffic.

Field Experiments of Connected and Automated Vehicle Systems

Field experiments on CAV systems are essential to better understand the actual behavior of CAV systems and obtain their performance characteristics. Those can range from small-scale experiments using a few connected or automated vehicles to large-scale deployment experiments such as the USDOT's Connected Vehicle Deployment Program. As an example for small-scale experiments, Milanés and Shladover (*50*) used up to four Nissan Infinity M56 ACC-equipped vehicles to generate vehicle response data to evaluate the performance of the ACC systems and build empirical ACC/CACC models. In another effort, James et al. (*41*) used 2 ACC-equipped Cadillac SRX vehicles to generate empirical data and calibrate their microscopic models.

Large-scale experiments provide even better understanding of the CAV behavior at the system level and are an integral step in the technology development and deployment process for collecting data on actual behavior and performance. In the case of the Connected Vehicle Deployment Program, for instance, thousands of different vehicles (personal, taxis, UPS delivery vehicles) in addition to hundreds of intersections will be equipped with a form of communication (V2V/V2I/V2X) to test different safety, mobility, and sustainability applications of connected vehicles. The program implements a comprehensive data management and privacy plans for the three different locations in New York City, Wyoming, and Tampa. The data to be collected through the program will inform public agencies, academics, and industry professionals on the potential impacts of connected vehicles and motivate future research using the data.

Chapter 6. Overview of Existing Analysis, Modeling, and Simulation Tools for Evaluating Connected and Automated Vehicle Impacts

This Chapter provides an overview of existing AMS tool that were used in the prior and current work reviewed in previous chapters.

Platforms and Special Purpose Tools

Because the impact of CAVs is so pervasive, at so many levels, tools by necessity entail the interaction of several different aspects and processes. To capture these interactions, model *platforms* are required, integrating various components relevant to the questions being asked (purpose of study). Platforms in this context are primarily conceptual analytical constructs that are embedded in a software tool. They typically entail a collection of models representing interacting agents or processes. Platforms also typically offer a foundation upon which additional capabilities may be built, albeit with varying degrees of difficulty and effort.

The transportation modeling domain has been dominated historically by two main types of platforms: (1) Modeling tools for planning, intended for application at the urban and regional level; and (2) Simulation models for operations, primarily applied to facilities or urban/suburban subnetworks. The former is typified by aggregate four-step models, which subsequently incorporated individual choice models for certain choice dimensions such as modal split, but with a highly simplified representation of congestion and operational aspects (*108*). The latter is typified by traffic microsimulation tools, which represent vehicular traffic interactions through individual maneuvers of car following, lane changing and gap acceptance.

These two strands started converging in the 1990's primarily through the development of simulation-based dynamic network traffic assignment (DTA) tools (*109*). These provide realistic representation of flow processes on links and at intersections, and individual level representation of individual travel choices of route, departure time and mode. Applicable to large networks, simulation-based DTA tools have continued to advance in terms of both representation as well as computational performance and have become the platform of choice for examining network and corridor interactions of user choices and traffic processes. Likewise, traffic microsimulation tools have moved towards DTA models by adding route assignment capability, and actually tracking vehicles from origin to destination instead of moving them probabilistically according to specified turning percentages.

Different physics have been used to represent flow processes in these platforms. The main differentiation has been in terms of detail of representation, with micro, meso and macro being the main labels for this differentiation. Macro models are essentially analytical relations between average quantities characterizing the state of a link or facility, whereas micro models move traffic as a result of context-dependent decisions made by individual driver agents. By moving individual vehicles (particles) at prevailing local speeds determined consistently with the respective prevailing local concentrations, typically using analytical relations, mesoscopic models retain the flexibility of individual vehicle or traveler representation with the convenience, robustness and ease of calibration of closed-form analytical equations. DTA tools have been developed with all three types of physics; the discussion here applies primarily to particle-based simulation, where individual vehicles/entities are tracked and used in conjunction with either meso- or micro-level physics.

The current state of the art, albeit not fully the predominant state of the practice, in transportation planning models consists of integrating simulation-based network DTA platforms with activity-based models (ABM) of travel demand and traveler behavior. An example implementation for the Chicago region is presented in Chapter 4. In practice, these tools remain only weakly integrated, if at all, with occasional interfacing for certain applications. Such integrated efforts are typically built on the network platform, i.e. the DTA tools, because computational efficiency of the resulting tool depends on the ability to execute path finding algorithms on large-scale networks.

Examples of simulation-based DTA platforms used in research, practice, or both, include DYNASMART-P and DYNAMIT-P, which were originally developed for FHWA to support ITS deployment studies. Both combine particle-based mesoscopic simulators with path finding algorithms for traveler route choice decisions; however certain important details differ, with important implications for ability to represent various aspects of CAV deployment, as discussed in Section 2.6. Both have continued active development to advance the state of the art, and many of the innovations introduced in these tools have been adopted as de facto standards in both other research tools as well as commercial offerings. Several offshoots of the original DYNASMART-P framework have been spun off, including VISTA, DynusT, DTALite, and DIRECT—all share the same modeling philosophy, though with possibly important differences for CAV impact modeling.

In addition to these university-generated tools, commercial platforms for meso-level DTA have emerged, generally as complement to static macroscopic assignment tools, or as add-ons to microscopic simulators. Examples include TransModeler (TransCad), DYNAMEQ (EMME), Cube Voyager, VISUM, among others (in parentheses are related static platforms by the same vendor). These are depicted in Figure 7, along the spectrum of micro-meso-macro. There is considerable variation across the commercial packages, which unfortunately tend to be somewhat opaque given the absence of documented refereed publications describing these tools. This is a limitation for CAV-related development, which requires detailed knowledge of and access to specific algorithmic components.

A third category of simulation-based network modeling tools, which were originally intended as agent-based activity-based demand models, includes the FHWA-funded TRANSIMS and its evolution into MATSIM in Switzerland. The latter adopts a non-standard cellular-automata traffic flow representation known to not be consistent with traffic flow theories, but allowing fast computation for large networks, albeit when not seeking to reach equilibrium states. It also allows flexibility to route agents and execute elaborate rule-based activity schedules.

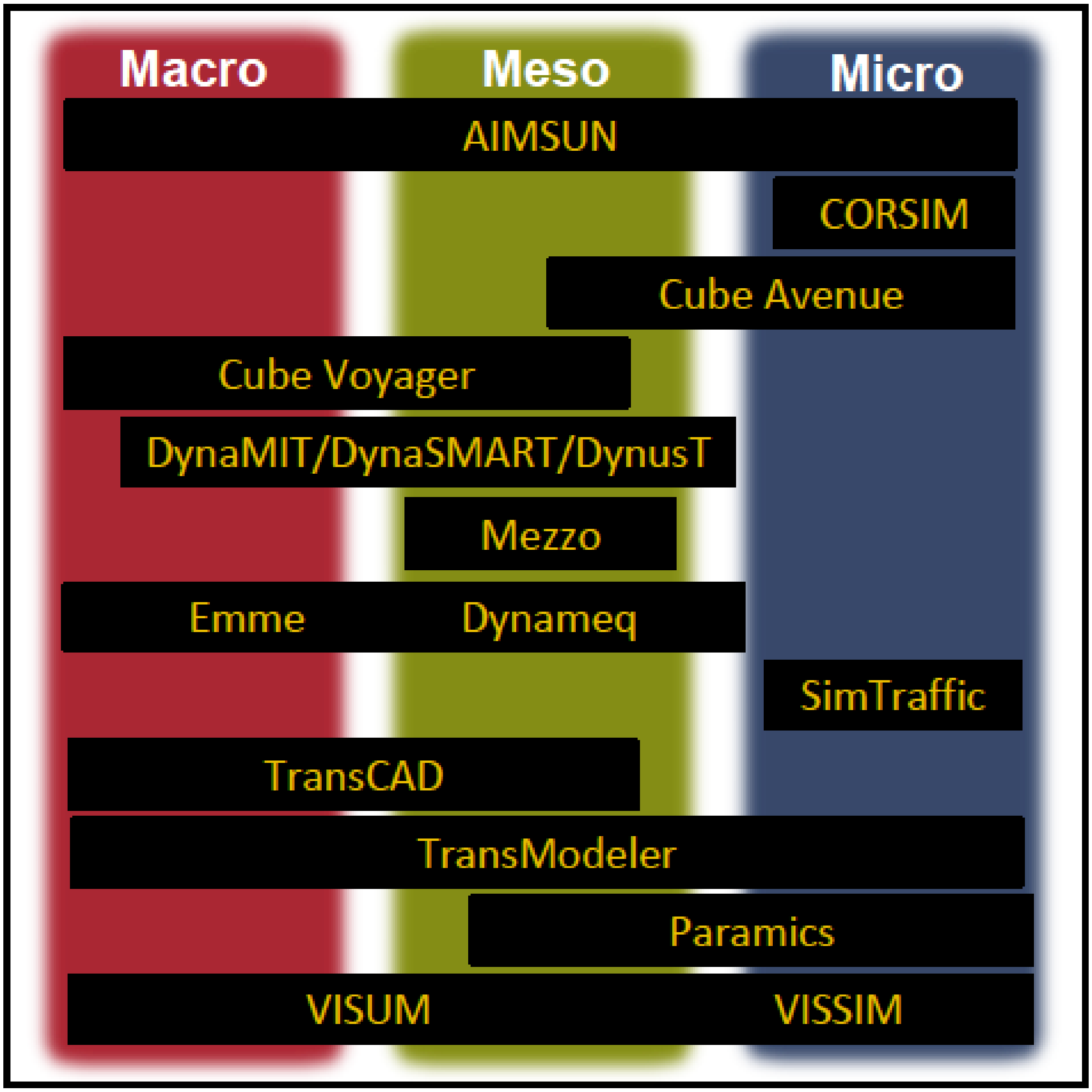

Figure 7. Range of network modeling platforms. (109)

In addition to DTA platforms, which have largely supplemented or co-opted static macro network tools for new model investment by agencies, the other major category of simulation platforms consists of microscopic simulation tools intended primarily for traffic operational applications. Originating in the 1970's with FHWA-supported NETSIM, which subsequently evolved into the current CORSIM, the domain experienced substantial commercial growth with the advent of ITS and adaptive signal control strategies that required fine-grained representation for design and evaluation. Three primary commercial platforms appear to dominate the market internationally: VISSIM, AIMSUN and PARAMICS. Like CORSIM and before it NETSIM, these are time-based, discrete event, discrete particle simulators, with heavy reliance on Monte Carlo methods to generate random variable realizations of a driver's every maneuver. With similar underlying logic (albeit different specific behavioral rules for drivers), the products have sought to differentiate through the quality and features of their graphical user interfaces, which continue to evolve to retain a modern, current look and functionality.

Other microscopic traffic operational microscopic platforms have also been developed and gained some traction, usually in specialized markets. These include TransModeler microscopic simulator, which is patterned in part on MITSIM, and is built on a based TransCad network; INTEGRATION, used primarily at Virginia Tech, which evolved from a mesoscopic version to a microscopic platform; Cube Avenue, and the open source SUMO (Simulation of Urban Mobility) developed at the German DLR Institute of Transportation Systems (*110*).

As expected, and as discussed in subsequent Chapters, off the shelf commercial packages for either strategic or operational applications are generally not capable of representing the particular aspects of CAVs that impact both operational performance and users' behavior. In some instances, modification of certain aspects through APIs is possible, but control of how the API is used in the overall simulation is generally not available. For this reason, researchers examining these questions have developed special-purpose tools focused on the particular questions of interest to their scope of study. These are typically not comprehensive or integrated platforms, but rather simplified representations of the future system in all but those aspects deemed by the researchers to be essential to their question of interest.

A key question for developers and agencies interested in developing a AMS capability for CAVs is whether to add CAV capabilities to existing commercial or otherwise established platforms, thereby taking advantage of graphical user interfaces and other useful components; or whether to take a special-purpose tool or component and integrate it in a larger, custom-targeted platform built around those capabilities. The simple answer to this question is "it depends"—on several factors, having to do with the structure and logic of the platform itself, and the degree to which the software could accommodate the desired features.

Essential Tool Components for Connected and Automated Vehicle Impacts

In the modeling framework discussed in Chapter 2. , four components (*26*) stand out in their significance for CAVs: (1) Demand Effects: Major Activity Shifts and Mobility Use; (2) New Mobility Industry Supply Options; (3) Network Integration; and (4) Performance (Flow) Models. These are depicted in Figure 8, and briefly explained below.

Demand Effects: Major Activity Shifts and Mobility Use

CAVs impact activity patterns at the individual and household levels in several ways (*55*) that may not be captured in existing demand models, even including the most advanced activity-based models (ABMs). Beyond the safety and efficiency aspects expected of CAVs (*8*), two key aspects that are likely entirely new with vehicles at automation levels (*15*) 4 and 5 are: (a) these vehicles enable multitasking, hence may change in-vehicle time valuation; and (b) their role as a robotic assistant for households and businesses (*58*), which can go shop, pick up kids– all mobility chores imposed by auto-centric suburban lifestyle. These features have implications on the demand side, for vehicle use/sharing within households. They require modeling the “Chauffeur” features of waiting and/or showing up when needed, possibly generating additional deadhead (repositioning) trips and VMT, even as the vehicle goes and waits in remote parking.

New Mobility Industry Supply Options

CAVs will enable new forms of mobility supply, such as new forms of car sharing with greater convenience than existing programs. Car-sharing marketplaces may emerge– e.g. driverless Uber. Reducing cost and uncertainty of the sharing model may reduce the motivation for individual ownership (*51; 82; 84*). Thus the realm between personal transportation and public mobility could widen considerably to include various hybrid forms (*61*). Scenarios regarding restructured public transit systems in which, for example, shared mobility services provide first and last mile access to higher frequency, high capacity lines become relevant, and must be represented using the AMS tools.

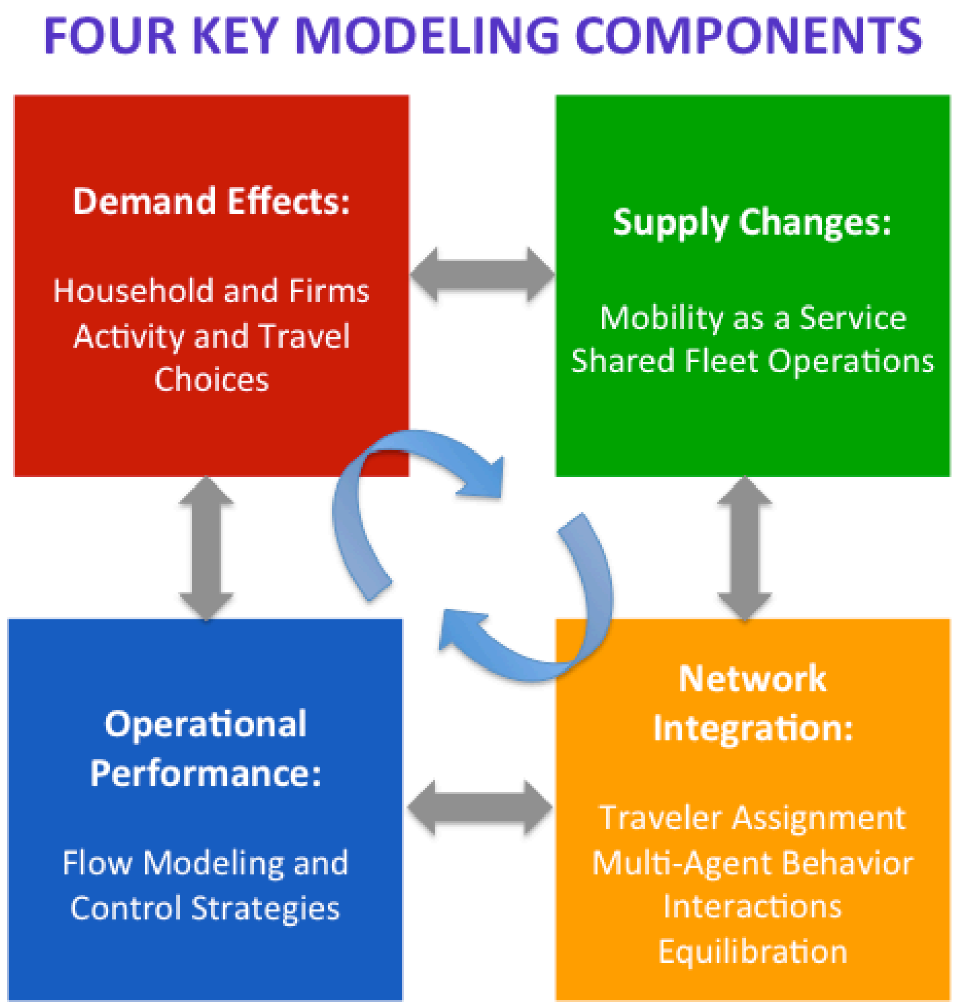

Figure 8. Four key modeling components of CAV impacts.

Network Integration

Integrating the behavior of different agents (travelers, mobility service providers, transit and network managers, freight shippers and carriers) in a network context in the presence of CAVs introduces many challenges that existing network modeling platforms may not be able to adequately address without varying degrees of modification. One basic question pertains to the appropriate behavioral notion for network assignment—for instance, would user equilibrium (UE) still make sense when fleet managers control the operation of large shared mobility fleets and could therefore seek routing policies that contributes the social (or system) optimum (SO), especially when vehicles are moving empty in repositioning moves? Some existing network modeling platforms that can explicitly allow multiple user classes with different assignment rules, including SO, and solve for the corresponding fixed points (equilibria), e.g. DYNASMART, would be able to represent these situations. However, many of the other tools have not implemented such multi-class equilibrium capabilities. Similarly, to reflect the role of mobility-as-a-service fleet managers, as well as the manner in which households share the use of automated vehicles, CAVs require tour-level, not trip-level network loading and routing. The same requirement exists for effective ABM-DTA integration.

Performance (Flow) Modeling

The most direct impact of CAVs on network performance will result from the operational performance characteristics of the vehicles in the traffic stream, and the control algorithms enabled by and deployed with varying degrees of V2V and V2I connectivity (*18*). While greatly dependent on decisions made in the commercial marketplace, public agencies, and regulatory bodies, understanding and modeling these impacts under a given set of assumptions about technological features, deployment scenarios and control measures is an essential AMS requirement that lies mostly in the realm of traffic physics. Several existing studies in the literature have attempted to address some of these questions, particularly with regard to throughput (*20; 37-42*), flow stability (*21; 24; 25*), and the performance of various control strategies (*43-46*) such as CACC (*17; 22; 47-50*) and speed harmonization (*101; 111*) in a connected environment. Flow modeling aspects require additional calibration as technology prototypes appear, and human behavior adapts in mixed traffic with CAVs.

Tools for Evaluating Supply Changes

The major supply change expected from deploying CAV technology is the emergence of new mobility options, mainly in the form of Shared Automated Vehicle (SAV) fleets (*53; 56; 57*). The emergence and adoption of CAVs has the potential to increase the market share of shared mobility service options via eliminating the cost and performance limitations of human drivers, enabling a broader array of service and price bundles. Many mobility service providers as well as tech companies and car manufacturers plan to employ AV fleets to provide transportation services. SAV differs from current sharing services in two main aspects: (1) the robotic driving behavior of vehicles is different from the human driving behavior, and will likely impact the overall performance of the system, and (2) the mobility service owner would have full control over the system, unlike services using human drivers, and can optimize the service to serve different objectives such as minimizing costs or maximizing quality.

To compete effectively with personal vehicle ownership in terms of cost and quality of service for all trip purposes, including the commute trip, fleet managers will seek to operate their fleets efficiently so as to minimize operational costs while maximizing quality of service. Different strategies can be devised for dynamically operating an AV fleet to provide passenger transportation service; these will depend on the business model of the provider and requirements for the services offered. Many potential AV fleet service options can be envisioned, varying in terms of one or more of their service dimensions, identified in the comprehensive taxonomy presented by Hyland and Mahmassani (*59*). These potential fleet business models are depicted in Figure 9. Additional strategic dimensions may include service area (city, suburbs, rural) and range of trips (short vs. long distance).

Three main aspects of mobility supply options would need to be addressed in an AMS system intended to examine CAV impacts: (1) Predicting the emergence of specific services (and their characteristics), along with shifts in the transit system, (2) Generating optimal plans to operate these fleets and services, and (3) Evaluating the impact of these services on the transportation system. The first of these is not within the capability of any tool, and must generally be handled in the form of input scenarios. The second is essential to emulate the manner in which the vehicles are deployed over the network, including the times and routes they follow. The third integrates the first two with a demand capability to predict network-level impacts on mobility and other metrics. The second and third aspects are often combined, with the latter serving as the performance evaluator for a given fleet operational strategy based on the former.

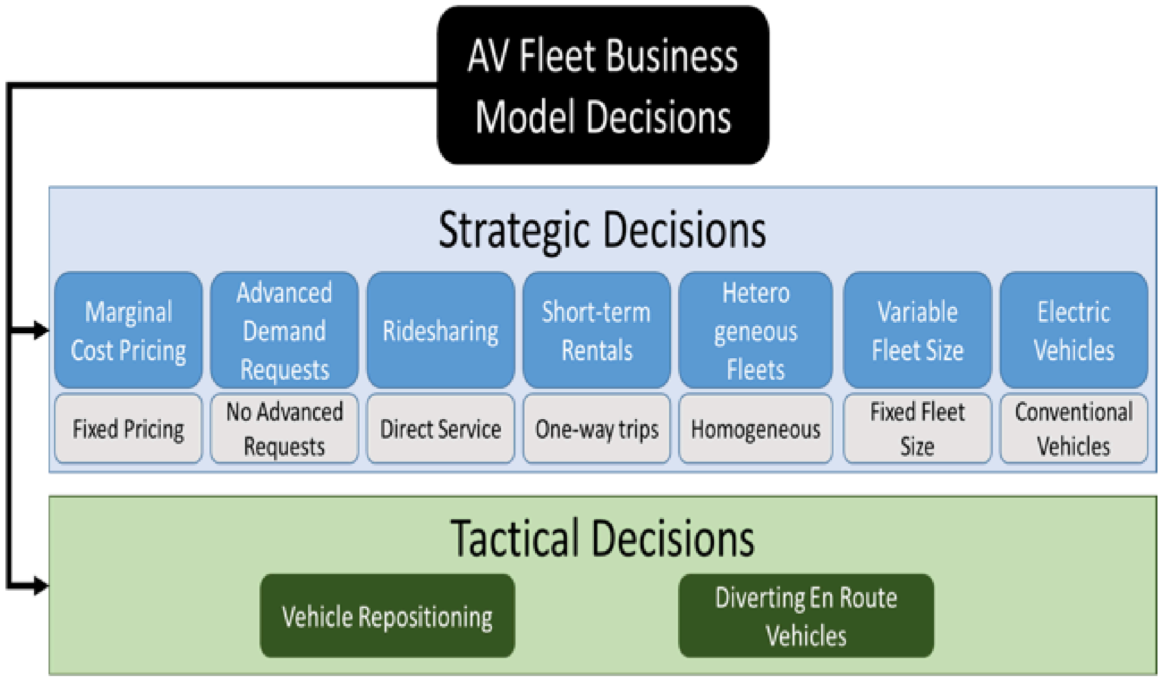

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Figure 9. Potential AV fleet business model variants. (59)

None of the above three capabilities are offered by general network modeling platforms. Algorithms for the second aspect (optimal fleet operation) could be devised through new implementations and application of some existing algorithms; however CAVs introduce unique elements that make direct application of existing procedures either infeasible or suboptimal. Despite the vast and diverse fleet management and vehicle routing literature, the nature of the CAV fleet operational problem is fundamentally different than problems in the existing literature. The notion of demand requests that require immediate assignment and pickup within a few minutes is not present in the *freight fleet management* and *dynamic vehicle routing* literature. Moreover, the demand requests in the existing passenger vehicle fleet management literature, such as the *dial-a-ride problem*, and even the *immediate request taxi-dispatch problem* (*112*) are significantly less urgent than the AV fleet problem. *Ambulance dispatching* and *ambulance fleet management* problems clearly match and exceed the urgency of the AV fleet problem; however, the ambulance fleet size and productivity/utilization of ambulances as well as the frequency of ambulance demand requests are much smaller relative to the AV fleet problem.

As noted, general AMS platforms do not have the capability to evaluate the impacts of SAV or analyze the system's operations. Therefore, most studies developed their own AMS tools to answer questions related to managing SAV fleets such as the number of vehicles required, travel time, costs, etc. Most of the tools developed are agent-based simulation platforms that capture the interactions between SAVs, travelers, and fleet managers (dispatchers).

An example of such tool is an event-based simulation framework built by Levin et al. (*60*) to examine the impacts of replacing personal vehicles with SAVs in downtown Austin, Texas. Another example of a CAV AMS tool built specifically built for modeling SAVs is the agent-based simulation platform introduced by Fagnant and Kockelman (*56*) to explore the potential impacts of dynamic ride sharing for a system of SAVs.

In both of the above studies, the dispatcher function relies primarily on simple strategies matching customers to the nearest vehicle; both employ ad-hoc idle vehicle repositioning strategies to re-locate empty CAVs to locations where the expected future demand rate is greater than the number of empty vehicles in the area. Such greedy rules can be shown to produce suboptimal results compared to more complete optimization formulations. Hyland and Mahmassani (*113*) have developed efficient dispatching strategies to operate an AV fleet. Their approach relies on an integer programming formulation that is solved in real-time to assign AVs to travelers. Further, these shared AV fleet services have been recently integrated within a multimodal transit network micro-assignment platform to capture the network-level impacts of these services for first/last mile access to restructured public transit lines (*114*).

Tools for Evaluating Demand Changes

The availability of new mobility forms through CAV systems (*27; 28*) in addition to the expected improvements to current transportation systems by the new technology can affect the activity patterns (*29-33*) and mobility choices of travelers (*34; 35*). Those changes can involve household-level decisions (*52*), such as owning a car (*51*), or individual trip decisions (*36*) such as departure time and route choice.

To evaluate the aforementioned impacts, researchers have mainly used two types of complementary tools(*115*): travel demand models (*83; 85*) and agent-based simulation approaches (*53; 54; 56; 81*). Demand models (including mode choice and activity based models) use current travel behavior, demographics, employment, and modes to project future demand patterns. Since actual travel data using CAVs is not yet available, CAV studies using these models rely on a number of assumptions regarding the characteristics of CAVs, and the relative magnitudes of travelers' preferential weights associated with these characteristics. These are sometimes based on stated preference, typically collected through surveys and more or less elaborate stated choice experiments. Thus, the forecasting power of these models is rather limited, as the assumed CAV characteristics and the stated travel behavior might be substantially different from the actual one when the new technologies become available.

Activity-based model (ABM) systems constitute the present state of the art in demand forecasting for planning applications. Several large metropolitan planning organizations (MPOs) have invested in the development of customized ABM capabilities. Implementations typically differ in terms of level of detail, and degree of complexity in terms of the choice dimensions and interactions captured in the model(*116*). Two well-documented examples include CT-RAMP (*117*), developed by PB Inc., and implemented in at least 10 metropolitan areas across the US, and CEMDAP (*118*), developed at UT-Austin primarily for applications in Texas and tested with NCT COG (North Central Texas Council of Governments, the MPO for the Dallas-Ft Worth region). The structure of the CT-RAMP version implemented for the Chicago area is depicted in Figure 10.

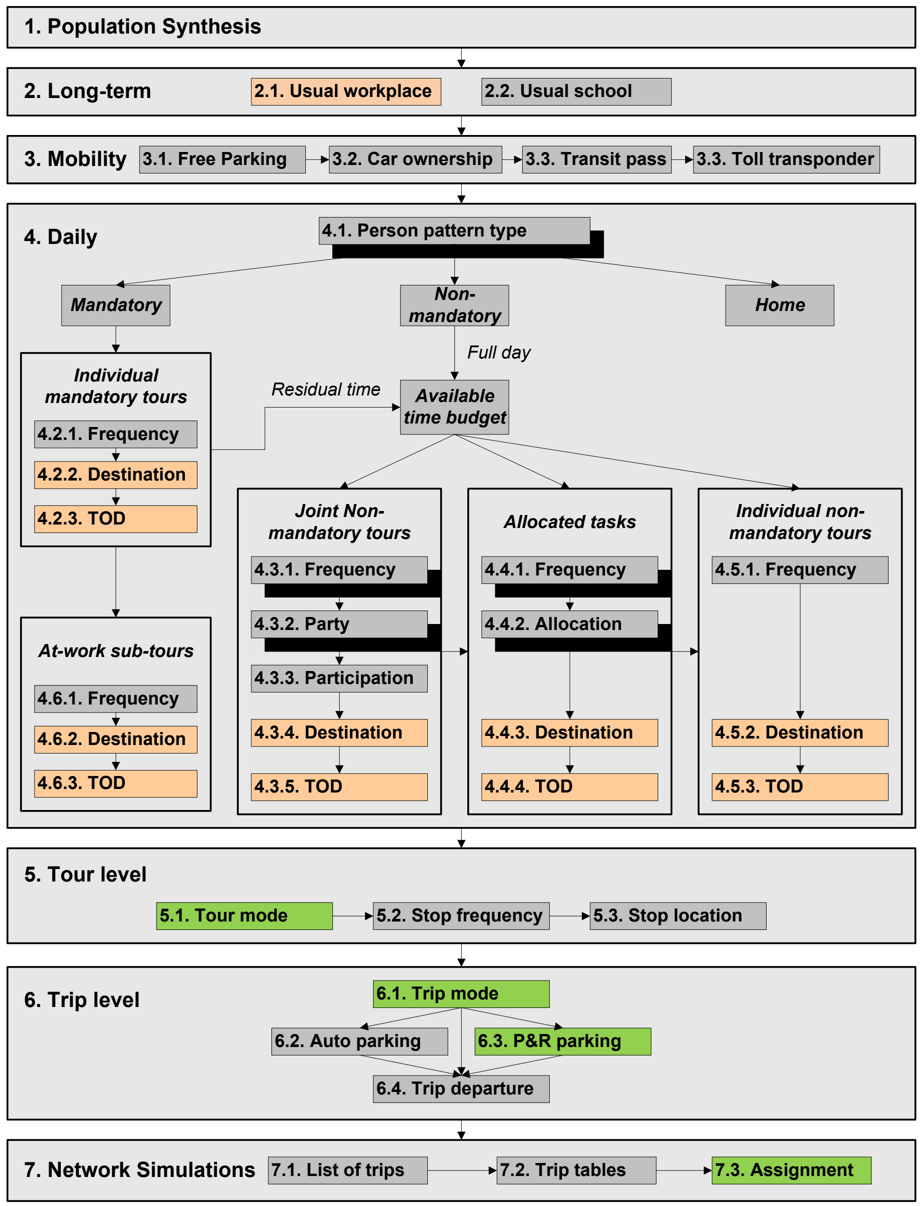


Figure 10. CT-RAMP activity-based model structure for Chicago. (117)

Demand models, especially the more elaborate activity-based model systems, are often implemented for forecasting purposes as part of agent-based simulations, where individual agents consist primarily of potential travelers. Accordingly, agent-based simulation tools are not really distinct demand forecasting tools as they ultimately depend on the behavioral engine driving the agents' simulated choices. For instance, implementation of individual-level choice models in the context of network particle simulation platforms would be an example of agent-based implementations.

Agent-based simulation approaches have been elaborated to answer specific research questions regarding CAV impacts through interactions amongst various agents. The main advantage of agent-based tools is that the rules of interactions between travelers (agents), travel modes, and the transportation network can be set/modified by researchers to adapt to CAV systems. While those rules are usually based on actual behavior, the interaction rules related to CAVs are usually assumed, or they may be based on limited field tests. This limits their ability to capture the potential travel behavioral changes anticipated with AVs; for instance, the "chauffeur" functionality, which might have drastic changes on intra-household activity and travel behavior, would be difficult to capture without actual data or sophisticated experimental approaches.

An example of demand models with CAV capabilities is the modified Seattle region activity based model by Childress et al. (*83*), which was used to explore the potential impacts of AV on Vehicle-Mile-Traveled (VMT) and Vehicle-Hour-Traveled (VHT). Another example is the modified Atlanta regional activity based model developed by Kim et al. (*85*). An example of agent-based implementations is the methodology developed by Chen et al. (*54*) to model the operations of electric-powered SAVs. The framework has four main modules: charging station generation, SA-EV fleet generation, waitlist, and strategic vehicle relocations.

Tools for Integrated Network Performance

Activity-Based Models (ABM) and Dynamic Traffic Assignment (DTA) procedures are advanced models on the demand and supply sides of transportation planning, respectively. While conceptually and theoretically inter-related, in practice these models have developed along essentially independent tracks. Simulation-based DTA tools allow modelers to incorporate disaggregate information into the estimates of travel costs that can be fed back into the ABM. Hence, most DTA tools used in practice have adopted a simulation-based approach to capture the dynamics of flow propagation in networks (*109*).

The need for achieving ABM-DTA consistency was recognized through the SHRP-2 C-10 project, which conducted two case applications of integrating different pairs of ABM and DTA tools. These applications addressed practical issues of interfacing tools developed independently and for different purposes, using inconsistent representations of the transportation system and the demand patterns using it. Their experience highlighted the challenges and practical difficulties in this process, and also brought out the need for stronger theoretical and methodological foundation on which to build such integration. Four follow-on projects were awarded to different areas as SHRP-2 C-10 was unwinding, with a focus on application issues pertaining to the specific areas. Interim conference presentations on these applications can be found at https://www.fhwa.dot.gov/planning/tmip/publications/other_reports/integrated_models/index.cfm.

One particular issue that is fundamental to such integration, and particularly relevant to the impact of CAVs, is how to achieve the equilibrium of users' schedules within the context of ABM-DTA integration. This issue was addressed in the ABM-DTA integration project conducted for the Chicago Metropolitan Agency for Planning (CMAP) (*117*). That implementation presented a novel equilibrium state definition for the ABM-DTA integration framework, and an algorithmic procedure to achieve it that takes into consideration individual schedule consistency between ABM and DTA as well as the usual equilibrium conditions in the multi-modal transportation network (*119*). Furthermore, it develops an approach for activity schedule consistency at the DTA level as part of an overall integration framework in order to improve the rate of convergence to the overall equilibrium state for the integrated model.

As households interact with CAV capabilities and new SAV options, the ability to model activity and tour schedules, and integrate them with the network modeling platform becomes crucial to the requirements of this project. The CMAP ABM-DTA tool allows that, taking advantage of a feature that has been available all along with the DYNASMART software, but it does not address the question of how the tours would be changed (as discussed in the previous section on modeling demand changes).

Likewise, it is essential for the CAV impact assessment platform to be able to route vehicles controlled by SAV fleet managers. As discussed earlier, it is not clear that User Equilbrium concepts are applicable to this situation. More importantly, there are interesting opportunities to improve overall system performance, and to nudge it towards a system optimum (SO) by controlling the movement of AVs, especially those driving empty to be repositioned or to their next pick up destination. As noted, a minimum requirement in this regard is the ability to allow different users or user classes to follow different assignment rules, including the ability to find fixed points or equilibria for such multi-class networks. These capabilities are reviewed in Chapter 4 along with those required for the demand changes.

Tools for Evaluating Operational Performance

CAV technology is expected to affect the operational performance of transportation systems in different aspects (*62*) including safety (*9; 63*), mobility (*1; 7*), and sustainability (*64*). The technology is expected to improve traffic safety through reduction of accidents caused by human error, increase throughput (*65*) through driving at higher densities with the help of highly responsive CAVs, and improve traffic control (*19*) at intersections (*67-74*) through wireless communications.

To evaluate those impacts effectively, however, the distinct behavior of CAVs (*23*) needs be captured in the AMS tools. Given the required detail at the individual vehicle level, the logical type of methodology consists of traffic microsimulation. Microsimulation provides the highest degree of detail in capturing the characteristics of CAVs including but not limited to car-following behavior, lane-changing, sensor range, wireless communications (*89*), reaction time, etc. It is the only type of simulation that is capable of simulating mixed traffic conditions at different CAV market penetrations as each vehicle is simulated individually. Therefore, most of prior/current studies on the operational performance impacts of CAVs relied on microsimulation tools. The main limitation for this type of simulation is the computing power it requires to process and analyze the high amount of detail associated with the simulated vehicles. This can limit the amount of time and the network size for which simulations are run.

However, for strategic-level CAV analyses of large regional networks, running detailed micro-simulation of all traffic maneuvers is neither necessary nor practical. Developing macroscopic relations for either facilities or networks requires observation of actual systems at different penetration levels of the technologies, which is not possible under the current situation—as these technologies remain in the very early stages of test deployment. Thus it is possible to rely on microsimulation experiments conducted for facilities and subnetworks to produce macroscopic fundamental diagrams and other performance characteristics that could then be used in conjunction with mesoscopic simulation-based network modeling tools to produce performance metrics at varying levels of spatial and temporal detail. Mesoscopic models provide a fidelity that is in between microscopic and macroscopic models. A recent example of incorporating the market penetration of connected vehicles in a mesoscopic tool was illustrated by Mittal et al. (*120*); the input speed-density parameters were generated using a special-purpose microsimulation tool (described in Chapter 5). Trajectories obtained from the network simulations then formed the basis for calibrating network-wide fundamental diagrams (NFDs).

In addition to modeling mixed flow impacts of CAV systems, modeling emerging traffic control and management strategies enabled by the new technology is also challenging. A particularly important aspect of emerging control algorithms is wireless telecommunications. However, most AMS tools lack an abstract representation of telecommunications in their models, its performance, and its impacts on driving behavior. Alternatively, they rely on specific assumptions about the V2V/V2I dynamics and the flow of information protocols, which can affect the realism of the control algorithms' performance. Microsimulation is also used in this case for modeling those strategies as it provides enough details to capture the interactions between the vehicle control devices (or the lack of them) and the infrastructure. Analyzing the emerging control strategies is done either by developing special purpose tools to evaluate specific control strategies or by integrating them into commercial platforms.

Commercially available simulation tools, such as VISSIM (*121*) from PTV and Aimsun (*122*) from TSS, do not currently have the capability to model CAV systems but will likely have that in the near future. However, those tools have means for enabling users to code their own models to represent special cases that are not included in the pre-defined default models, which are a primary mechanism for current researchers interested in using these tools to evaluate CAV alternatives. However, the parameters for these models would still need to be assumed, as the data required to calibrate these models is not likely to be available in the near future.

In addition to coding special CAV characteristics into existing tool, some researchers have developed simulation platforms that are specifically designed to model mixed traffic with CAV systems. An example of that is an integrated simulation platform developed at the Northwestern University Transportation Center that is capable of modeling human, connected, and automated vehicles in addition to modeling V2V/V2I wireless telecommunications.

Chapter 7. Identified Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities

This chapter identifies the main gaps where existing capabilities do not meet those required for the envisioned CAV AMS system. The envisioned CAV AMS system is an integrated system developed in Task 3 to fulfill the needs of users, researchers, and model developers for evaluating the far-reaching impacts of CAV technology on multiple levels. The system is discussed in detail in the Task 3 reports (*5; 6*).

Following the structure of the methodological framework introduced in Chapter 2. , this chapter categorizes the identified gaps in CAV AMS capabilities into four main areas:

1. Gaps in evaluating demand changes
2. Gaps in evaluating supply changes
3. Gaps in evaluating operational performance
4. Gaps in evaluating integrated network performance

The remainder of this chapter will discuss the gap identification process and the main gaps in each category and their potential impacts on CAV AMS. In addition, the chapter will briefly discuss suggested approaches to address those gaps.

Connected and Automated Vehicle Analysis, Modeling, and Simulation Gap Identification Process

The gap identification process in this project is a multi-step process that builds on the reports of previous project tasks (*2; 3; 5; 6*). The first step was to identify user needs for CAV AMS. Those mainly include the (1) capability to evaluate strategic impacts of CAV systems, such as the activity pattern changes and the emergence of new mobility options, (2) the capability to evaluate tactical/operational impacts in the presence of mixed traffic flows, and (3) the integration of all system components to better capture the interactions among the different agents (travelers, mobility service providers, transit, etc.) in a network context. The user needs identification was performed in Task 3 (*5; 6*) where a comprehensive methodological framework was formulated for evaluating the strategic (supply and demand) and operational impacts of CAV systems.

Furthermore, the requirements of an envisioned CAV AMS system were identified in the same task. Those include functional, performance, data, and integration requirements. Identifying the user needs and the system requirements in above-mentioned task was essential for conducting the gap analysis in this report. In addition to providing a vehicle for discussion and stakeholder engagement, the identified needs and system requirements were later used as a benchmark for identifying gaps in existing AMS tools.

The second step was to conduct a comprehensive review and assessment of existing CAV AMS capabilities. The comprehensive review included an overview of related literature, reports, and planned activities relating to CAV AMS that was done in Task 4 (*2*). The review also included an identification/assessment of existing and emerging data sources which are required to support CAV AMS, which was done in Task 5 (*3*). While supporting data is fundamental for the development, validation, and operation of AMS tools, it is even of higher importance in the case of CAV systems as the data related to their operations/impacts are very limited. Finally, the comprehensive review included a capability identification of existing AMS tools for analyzing CAV applications at the strategic and operational levels in Task 6 (*3*). In this task, the identified capabilities of existing tools, whether they are platforms or special-purpose tools, were assessed based on the requirements of the envisioned CAV AMS system introduced Task 3 (*5; 6*).

The final step of the gap identification process, which is the main part of this report, is to consolidate the findings of previous reports to identify the main areas where existing capabilities do not meet the identified requirements for evaluating the impacts of CAV systems. In addition, the report assesses the identified gaps across different dimensions to better understand their impacts. Those dimensions include the level at which the gaps exist, whether being a platform-level or component-level, and the type of the gap, whether it is methodological, data-related, or implementation-related. Finally, the report provides an initial recommendation on prioritizing those gaps and potential solutions to address them. The remaining of this chapter provides descriptions of the different dimensions across which the gaps were assessed. The gap identification process is summarized in Figure 11.

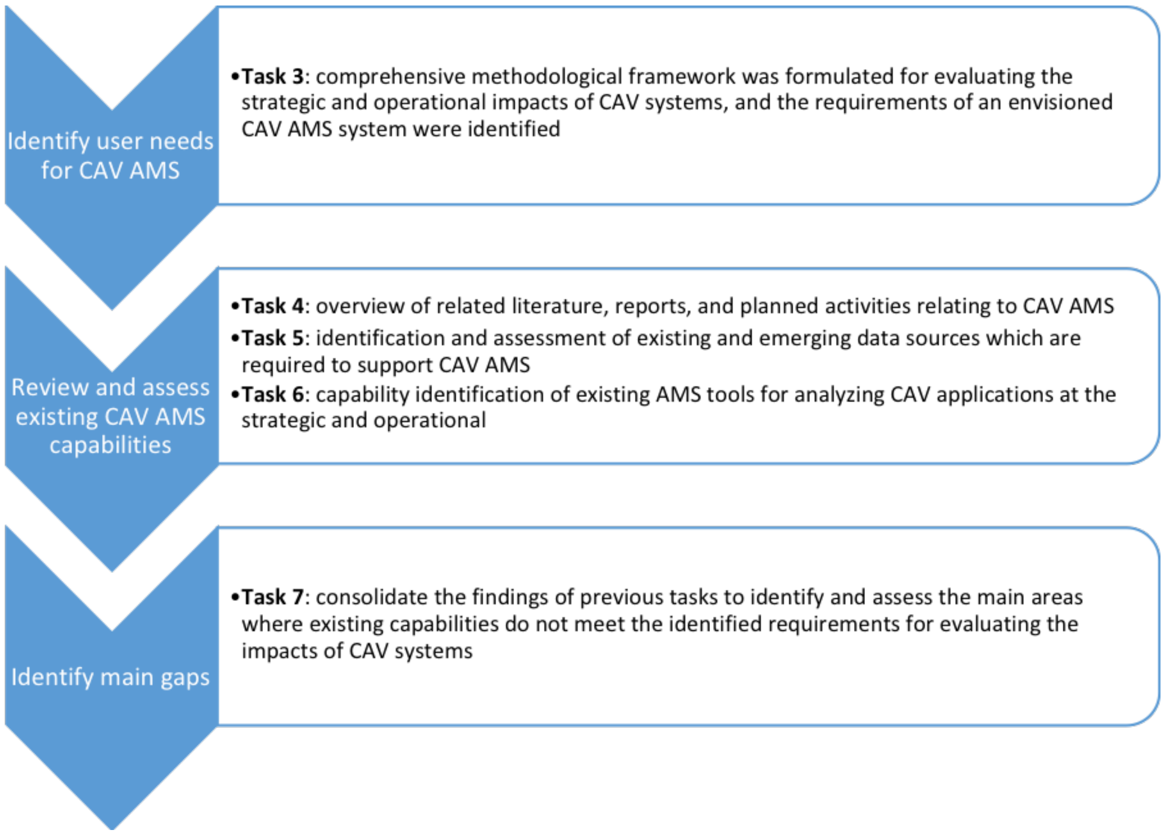


Figure 11. Gap identification summary.

System Level: Component and Platform

The envisioned CAV AMS system has four main components for modeling the impacts of CAV systems on the strategic and operational levels. Three of those modeling components provides distinct functionalities for modeling the supply, demand, and operation related impacts of CAVs while the fourth component is related to integrating all of the above three components at a platform level. A platform in this context is primarily a conceptual analytical construct that is embedded in a software tool. It entails a collection of models representing the interactions among different agents/processes.

Component-level gaps refer to those related to any of the three specific components in the envisioned CAV AMS system: demand changes, supply changes, or operational performance. For example, integrating the multitasking feature of automated vehicles is a gap that is specifically related to modeling the demand change component of the system and therefore is considered a component-level gap. On the other hand, integrating the operational performance impacts of CAV systems in demand models to produce more realistic impacts is a platform-level gap as it relates to how the system functions as a whole. The differentiation of those gaps with respect to their level is important to determine how to approach and prioritize those gaps.

Gap Type: Methodological, Data-related, Implementation-related

Three main types of gaps were identified in existing CAV AMS capabilities: methodological, data-related, and implementation related. Methodological gaps refer to those where fundamental and unique aspects related to CAV systems are missing from current models or tools. For example, the multitasking functionality is a unique feature of AVs that is often missing from current demand models or not explicitly/appropriately represented. Wireless telecommunication and sensor reliability are two examples of the fundamental features of CAVs that is often missing in performance models.

Data-related gaps refer to those where the modeling capabilities exist or are relatively developed but the supporting data to validate/calibrate those capabilities are not available. For example, many car-following models were developed to represent CACC driving behavior, however, empirical data for validating those models are often missing except for few cases where small-scale field studies were conducted. Another example is lack of data on the impact of the anticipated “Chauffeur” feature of AVs on household activities.

Implementation-related gaps refer to those where the capabilities exist but are not implemented to capture the full interactions of CAV systems. Those gaps are mainly related to the integration of different modeling components such as integrating traffic flows generated from demand models in performance model to evaluate their network impacts.

Gap Prioritization

The gap analysis in this report offers a preliminary prioritization of gaps from the point of view of the research team. Three priority levels were considered: (1) critical, (2) important, and (3) desirable. Critical gaps refer to those that should be addressed as a first step for developing a CAV AMS system. For example, the lack of supporting data to validate CAV car-following and lane-changing models is critical for an accurate evaluation of the performance impacts of CAV systems. Important gaps refer to those that are not as essential as critical gaps but are important for an improved representation of CAV systems, such as the lack of practical and simplified representation of the effect of wireless telecommunications on the performance of CAV systems. Desirable gaps refer to those that are important to be addressed in the longer term such as predicting the emergence of new mobility options.

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Demand Changes

The new forms of mobility (*27; 28*) enabled by CAV technology and their expected improvements to the performance of transportation systems could lead to fundamental changes to the transport-related decisions. Those changes could affect the activity patterns (*29-33*) and mobility choices of travelers (*34; 35*) at multiple levels. On the higher level, the potentially improved features of the new mobility options, such as the higher safety and lower costs of SAVs, could affect household car ownership (*51*). On the tactical level, some of the new features of AVs - mainly the availability to multitask during the trip - can affect individual trip decisions (*36*) such as departure time and route choice.

Researchers have mainly used two types of complementary tools (*115*) for evaluating the abovementioned impacts: travel demand models (*83; 85*) and agent-based simulation approaches (*53; 54; 56; 81*). Demand models (including mode choice and activity-based models) use current travel behavior, demographics, employment, and modes to project future demand patterns. Since actual travel data using CAVs is not yet available, CAV studies using these models rely on a number of assumptions regarding the characteristics of CAVs, and the relative magnitudes of travelers' preferential weights associated with these characteristics. Agent-based simulation approaches have been elaborated to answer specific research questions regarding CAV impacts through interactions amongst various agents. While the interaction rules in those tools are usually based on actual behavior, the rules related to CAVs are usually assumed, or they may be based on limited field tests.

The above-mentioned tools help answer some of the main questions related to the demand changes that are expected with the deployment of the new technology. Those include questions related to the adoption of the new technology (*27; 28; 35; 81; 82*), travel mode shifts (*34; 36; 83*), vehicle ownership (*52-55*), and VMT impacts (*27; 31-33; 54; 55; 64; 83; 85*).

The main limitations of existing CAV AMS capabilities for evaluating the demand-related impacts of the new systems are mainly related to (1) the lack of data on the unique characteristics of CAVs and (2) the explicit integration and validation of the multitasking feature of AVs in those capabilities. Those limitations are discussed in more detail in the following gaps.

Data Describing the Unique Characteristics of Connected and Automated Vehicle Systems as a New Option in Demand Models

One of the main gaps in evaluating the potential demand changes caused by CAV systems is the lack of data on the unique characteristics of CAV systems as a new mode in existing AMS tools. Those characteristics generally make the new CAV-enabled modes safer (*9; 63*), more sustainable (*64*), and more economical (*26*) than current options. For example, AVs are expected to reduce/eliminate roadside accidents that are caused by human error (*8*). They are also expected to reduce emissions through smooth acceleration/deceleration (*53*) or through economical traffic control algorithms such as ECO-CACC (*102*). The cost of SAV trips can potentially be lower than those made by current shared ride system or hailed-ride systems as it eliminated drivers' costs.

While existing AMS capabilities integrate some of the unique characteristics to evaluate the impacts of the new systems, the extent to which those characteristics affect the different parameters in the tools is usually assumed and not based on actual observation. Some of those assumptions are based on performance (simulation) models that are also usually not validated using actual data. For example, some modified activity-based models integrated the AV mode by increasing the capacity of the road by a certain percentage, reducing operational costs, or in-vehicle time utility (*83; 85*). Other simulation tools have implemented similar assumptions regarding the performance of CAV systems (*32*).

Using different assumptions regarding the characteristics of the new systems instead of basing these assumptions on actual observations can have profound impacts on the prediction accuracy of the demand changes caused by CAVs. This is because most of these unique CAV characteristics such as lower cost, different travel time value, or higher comfort are directly related to the mode choice and travel behavior. For example, using a very low value of travel time for AVs may overestimate the mode shift towards those vehicles. It may also overestimate the impact on VMT as travelers may tolerate longer distances in AVs. Similarly, using a lower than actual assumption about travel costs for SAVs may overestimate the shift towards those vehicles and the reduction in household car-ownership.

This gap would be classified as occurring at the “component-level” as it is mainly related to the Demand Changes component of the envisioned CAV AMS system. This gap is considered “data-related” because existing AMS capabilities would be able to integrate the unique characteristics of CAVs had data on those characteristics been available. Finally, the initial priority to address this gap is “important”; while it can affect the impact evaluation accuracy of any AMS tool regardless of its complexity or its interaction rules, collecting the data necessary for demand models highly depends on the actual deployment of the systems.

Potential Ways to Address this Gap

Addressing this gap may require performing field experiments to collect actual data. Since CAV systems are not deployed in the field yet, this could be done using prototype systems or commercial systems with automated cruise control. For example, CAV prototypes such as those tested by Uber[i]

Vehicles with commercial ACC can be used to estimate the actual fuel consumption and estimate lower costs. This may also require a fully comprehensive life cycle analysis to estimate those costs. In addition, simulation tools can also be used to extract CAV characteristics if those tools are validated/calibrated using driving behavior data of actual CAVs.

For estimating value of travel time, a mode choice experiment using a stated preference survey can be used. The respondents would be presented with hypothetical trips (distance, cost, mode) where AV as one of the available modes. Those scenarios should cover a wide range of trip for different purposes. For example, long work trips, short shop trips, long recreational trips, etc. The answers to those questions can then be used to estimate the value of travel time for AVs. It is worth mentioning; however, that in the case of stated preference survey, the answers may not reflect actual behavior and therefore may affect the estimated values.

A last-resort option, which is implemented by most studies when faced with uncertainty about some of CAV characteristics is to develop multiple scenarios/values for those characteristics and evaluate their impacts. While this method is the cheapest/easiest to provide a range of impacts to reduce the uncertainty and is better than using one assumed value that may be incorrect, it does not solve the root of the gap which is the lack of validated data.

Integrating the Multitasking Feature of Automated Vehicles in Demand Models/Components

The second major gap in current CAV AMS capabilities is explicitly integrating the multitasking feature of AVs in demand models or the demand component of AMS systems. Multitasking is maybe the most important characteristic of AVs with potentially the highest impact on the activity pattern shifts. Travelers would no longer be constrained by the unproductive time spent in their personal vehicles. On the contrary, owners of AVs would have access to an entirely new feature in the form of a robotic “Chauffeur” that may change the whole prioritization/sequence of their activities (*26*).

This important feature is missing in most existing CAV AMS capabilities. Some activity-based models implicitly integrated this feature in a scenario where the value of in-vehicle travel time was reduced (*83*). However; this approach suffers from critical limitations as (1) it does not capture the interactions among different agents in a household and their actual travel decisions with respect to AVs, and (2) this time value is often assumed and not based on observed data.

Omitting the multitasking feature in CAV AMS tools can significantly affect the prediction accuracy of the new technology’s impacts on VMTs, mode-shifts, and household car ownership. As the main AV feature that could affect the value of in-vehicle travel time (*29*), the lack of methodological integration within AMS tool may lead to overestimating/underestimating the impact on VMTs. This also applies to mode shifts the time value is a critical factor for mode choice.

This gap can be categorized at the “component-level” as it entails integration with the Demand Changes component of the envisioned CAV AMS system. The gap is also “methodological” one as existing AMS capabilities do not systematically capture this feature but rather use implicit approximations like changing the value of travel time. As the main feature of AVs with the most potential for causing activity shifts, addressing this should be one of the early steps for building the envisioned CAV AMS systems and therefore the gap is classified as “critical”.

Potential Ways to Address this Gap

Addressing this gap requires an explicit integration of this new feature within demand models or the demand component of AMS systems. This could be accomplished by relaxing the activity sequencing constraints in demand models. This could be easier in the case of agent-based simulation models where the activity sequence relaxations can be implemented within the interactions rules of the agents. Alternatively, it could be implemented as a resource (additional time) that may be allocated to activities. This may require significant change in how interaction rules are specified and programmed in simulation models.

Data Describing the Impacts of a Robotic "Chauffeur" on Household Activity Prioritization and Sequencing

As mentioned in the previous gap, the multitasking feature of AVs will enable an entirely new transport feature in the form of a robotic “chauffeur” (*5; 26*). This new form of mobility allows easier sharing of vehicles at households and can be used as an extra resource to help with family tasks around the household. For example, an AV can be used to drive one household member to their work and come back to pick up the other after or an AV can be used to drop off kids to their schools.

Household car ownership predictions can also be affected since household members can potentially share their vehicles more efficiently or substitute it with an SAV. Therefore, they may require using less number of vehicles. All of these new scenarios that are enabled by the new technology requires an entirely different modeling approach to capture their impacts on household activities.

In addition to methodologically integrating the new multitasking (or robotic chauffeur) feature in demand models/components, as discussed in the previous gap, it is equally essential to collect data to validate the impacts of the new feature on household activity patterns or shift. The robotic chauffeur feature enables numerous scenarios where household members can utilize to maximize their productivity or convenience. However, the extent to which those scenarios will apply is unknown. For example, parents might be able to send their kids to school with an AV and demand tool should capture that. However, parents may actually not trust that technology enough to do so. Therefore, without actual data to validate the new features in the model, their impacts will likely be inaccurate.

In the case of evaluating household car ownership, for instance, assuming that household members will always share an AV whenever possible without actually validating that with actual data (or at least stated preference data) may overestimate the reduction in car ownership. Similarly, it may overestimate VMTs due to the extra empty miles traveled between trips of household members.

This gap is a “component-level” gap as it is mainly related to the Demand Changes component of the envisioned CAV AMS system. As explained in the aforementioned discussion, this gap is both methodological and data-related due to the lack of actual data to validate the impacts of the new multitasking (robotic chauffeur) feature, which in itself is not yet explicitly integrated into demand models/components as discussed in the previous gap. The gap is classified as “critical”. Integrating the feature in the models without actual data to validate it will allow sensitivity analyses to be performed, and provide ranges for the likely impacts. Given that this is potentially one of the most significant features in terms of impact on household interactions and role of mobility tools in these interactions, it is critical to address this gap to support assessment of CAV impacts at the strategic level, and consideration of their implications for long-term planning.

Potential Ways to Address this Gap

Collecting actual observations or revealed preferences regarding the multitasking feature of AVs will not be possible in the short-term because the highly automated vehicles do not exist yet for consumers. Therefore, the more immediate option would be to collect household preferences and potential travel behavior changes as a result of the new technology through hypothetical scenarios in a stated preference survey. In this survey, travelers would assume that they own an AV with a robotic chauffeur feature and then asked about how they would schedule their activities knowing that they have this new capability. As is the case with all stated preference survey, the hypothetical scheduling may be different from the actual one. However, this would be a first step to calibrate the demand models/components once the multitasking feature is integrated.

A more expensive option, with potentially more accurate data, is to simulate an AV by having a driver that is always available to a household. This way, households would have the ability to experience the chauffeur feature and actually plan their activities with that in mind. Having a human driver, however, may have a different effect than a robot. For example, some parent may trust a human to drop their kids at school while others may trust a robot more than a stranger. Furthermore, this experiment can be done for specific parts of the day only, morning/evening peak hours, for example, to validate the impacts on specific trips.

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Supply Changes

The major supply changes expected from the deployment of CAV systems pertain to the emergence of new mobility options. This is mainly in the form of a Shared Automated Vehicle (SAV) fleets, and hybrid systems enabled by the new form (*53; 56; 57*)., such as for example, an integrated transit-SAV system where the latter serves as a first/last mile connection. While shared vehicle fleets are not an entirely new form of mobility, transport network companies (TNC) such as Uber and Lyft already offer this service, SAVs have two main differentiating features: (1) the robotic driving behavior of vehicles is different from the human driving behavior, and will likely impact the overall performance of the system, and (2) the mobility service owner would have full control over the system, unlike services using human drivers, and can optimize the service to serve different objectives such as minimizing costs or maximizing quality. These two features have the potential to increase the SAV market share and competitive advantage against other modes.

Three main aspects of mobility supply options would need to be addressed in an AMS system intended to examine CAV impacts: (1) Predicting the emergence of specific services (and their characteristics), along with shifts in the transit system, (2) Generating optimal plans to operate these fleets and services, and (3) Evaluating the impact of these services on the transportation system.

The first of the above aspects is beyond the capability of any tool and is one of the main gaps in existing CAV AMS capabilities. The second aspect is what most studies have focused on (*59*) by building special-purpose simulation tools (*54; 56; 60; 61*) to answer questions related to managing SAV fleets such as the number of vehicles required, travel time, costs, etc. The third aspect is achieved by integrating the first two aspects with the demand component in an AMS system to evaluate the impacts at a network level.

The gaps with respect to modeling the supply changes in a CAV AMS systems is (1) the inability of current AMS systems to predict the emergence of new mobility systems enabled by the new technology and their characteristics, and (2) incorporating wireless telecommunication in the infrastructure representation as it is an essential element of CAV systems. The remaining of this section will discuss the gaps in further details.

Predicting the Emergence of New Mobility Options Enabled by Connected and Automated Vehicle Systems and their Characteristics

The rapid development in wireless telecommunication technologies and the high adoption rate of those technologies have enabled radically new forms of mobility and opportunities for multi-mode integrations that were not possible or thought of less than 20 years ago. Most AMS tools, for example, failed to predict current ride-hailing services, such as Uber and Lyft, which were only enabled by advancements in positioning, telecommunication, and handheld computing technologies.

The current development in the areas of artificial intelligence, robotics, CAV systems, and the internet of things will probably cause even more radical changes to the forms of mobility that travelers are used to. Aside from more futuristic modes such as flying cars or the Hyperloop, the most anticipated mode enabled by the aforementioned technologies is SAV fleets.

Current CAV AMS tools are unable to predict some critical characteristics of SAV fleets such as costs, travel time, comfort, or charge range (for electrical vehicles). Instead, these tools focus on modeling the operations of SAV fleets under multiple assumptions about those characteristics, network configuration, and wireless telecommunications. Furthermore, current AMS tools are unable to predict emerging multi-mode integrations such as a transit and SAV where the latter provides a last/first-mile solution.

The inability to predict the afore-mentioned changes with respect to the supply options may significantly affect the ability of CAV AMS systems to predict their strategic or operational impacts. Some of the unanswered questions would, for example, whether the new service will be optimized towards the comfort of the traveler or to maximize the profits of the operator, or whether the service will only be located in dense areas vs. serving those in less populated area. Furthermore, the inability to predict potential multi-mode integration can lead to missed opportunities for optimizing the transportation system as a whole.

This gap can be considered a “component-level” gap as it is mainly related to the Supply Changes component of the envisioned CAV AMS system. The gap is also “methodological” as it does not a feature of any CAV AMS capabilities. While predicting new modes and their characteristic is important for a comprehensive evaluation of their impacts, building such a capability can be a very complicated process. The prediction would rely on multiple factors such as market trends, technology development, and political will. Therefore, this gap is prioritized as “desirable.”

Potential Ways to Address this Gap

As developing a full capability to predict emerging mobility option can be a very complicated process, one way to partially address this gap is to develop multiple operational scenarios of the new modes. Those scenarios will be based on current and predicted market trends, technology development, regulations, and ultimately expert judgment. Therefore, it is critical for the envisioned CAV AMS to be able to define and test different scenarios that will determine the availability of new modes and the type of telecommunication technology in place, whether it is V2I, V2V, or V2X communications. This should lower the uncertainty in the impacts of those modes.

Data Describing the Unique Characteristics of Connected and Automated Vehicle Systems Integrated into Fleet Management Modeling of Shared Automated Vehicles

One of the major limitations of current simulation tools modeling the operations of Shared Automated Vehicle (SAV) fleets is the lack of actual data describing the characteristics of anticipated AVs. While some prototypes are being tested in the field by private TNCs, those the data used from those experiments are usually inaccessible to the public. An example of those characteristics is the actual travel time by SAVs on the network, which highly depends on the performance of those SAVs in traffic. Furthermore, current AMS tools mostly rely on simple rules that a central dispatcher uses to assign SAVs to travelers (*56; 60*). In practice, fleet operators are likely to use an optimization approach to minimize their operating costs. Therefore, the simulated movement of SAVs on the network in current agent-based tools may be different from actual operations.

Using actual data to validate the rules/formulations used in tools is essential for generating optimal fleet management plans, and consequently, better evaluations of their impact on the network. For example, using simple rules to assign SAVs to travelers, such as on a first-come-first-serve basis, would require vehicles to travel extra miles to serve the requested trips and therefore increase VMTs. It may also affect the number of vehicles required to serve those trips and the estimated costs. Those impact will likely be overestimated if operators opt to optimize their operations with advanced assignment algorithms such as those being developed in some of the more recent work by Hyland and Mahmassani (*113*). Another characteristic that is missing from existing tools modeling electric SAVs is the network of charging stations and the charge range of those vehicles. Current tools (*54*) rely on a hypothetical network of charging stations and assumed ranges. Both of those critical aspects may be different once the technology is deployed.

This gap is considered a “component-level” gap as it is mainly related to Supply Changes component in the envisioned CAV AMS system. The gap is also “data-related” as per the above discussion. Finally, this gap is prioritized as "important" since the missing data on the above-mentioned characteristics highly affects the operations of SAVs and their impacts on the network. However, the network impacts are likely to be long-term when/ if SAVs become a dominant travel mode.

Potential Ways to Address this Gap

Reaching out to TNCs, such as Uber and Lyft, might be the most effective way to gather information on the expected characteristics of the SAVs. Those companies are likely to be the first adopters of the SAV technology as they have invested in it and integrated it as part of their future business models. While TNC may not disclose some information that is critical to their competitive edge in the market, they can provide some important insights about the type of technology they are looking for in the future and some general operation strategy.

Incorporating Wireless Telecommunication in Infrastructure (V2V/V2I/V2X)

Another feature of CAV systems that is missing in almost all existing CAV AMS capabilities is incorporating wireless telecommunication as in the representation of infrastructure and networks. Reliable wireless telecommunication is not only essential for the operation of CAV technologies but can also affect the driving behavior of CVs. Most AMS tools, especially SAV fleet modeling one, just assume that all vehicles are connected and the central dispatcher has full information regarding the location of all vehicles, requests, origins, and destinations. This may not be the actual case in practice.

If DSRC technology is used for V2I telecommunications, it will likely be deployed in strategic locations due to its high costs which will impact the operations of SAV fleets that rely on a central dispatcher to assign vehicles. Furthermore, wireless telecommunications, even the most advanced technologies to date, may not reliable at all times. It may suffer from outages, disconnections, or poor signals, especially at severe weather conditions. Similar reliability issues involve the positioning of vehicles such as lost GPS signals inside tunnels.

Having an abstract representation of wireless telecommunications in CAV AMS systems is important for a realistic representation new mobility options and evaluating the telecommunication impacts on driving behavior. In other words, this gap is related to both the Supply Changes and Operational Performance components in the envisioned CAV AMS system and therefore is considered a “platform—level” gap and is prioritized as “important”. It is also classified as a “methodological” gap since wireless technology is a unique feature of CAV systems that is not represented in almost all exiting CAV AMS capabilities.

Potential Ways to Address this Gap

This gap can be addressed by integrating a set-up of wireless telecommunication technologies (V2I/V2V/V2X) within the network representation. This is particularly important in the case of DSRC communications. They can be designated nodes or links within the network where those technologies are strategically installed. The designated nodes/links should also include communication ranges which would affect the information flow between connected agents (travelers, vehicles, infrastructure). Those strategic locations within the network would also affect the driving behavior of vehicle within those ranges. The exact method to be used for representing wireless telecommunications in network configurations is an interesting topic for future research.

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Operational Performance

CAV systems are expected to improve different performance aspects (*62*) of transportation systems including safety (*9; 63*), mobility (*1; 7*), and sustainability (*64*). The technology promise to reduce accidents that are caused by humans, improve road capacities by driving safely at higher densities (*65*), and improve traffic control whether on freeways or intersections (*19; 67-74*).

To evaluate the above-mentioned impacts, the unique behavior (*23*) of CAV systems needs to be captured at the individual vehicle level in AMS tools. Therefore, most researchers relied on microsimulation tools which offer the highest fidelity to comprehensively capture the characteristics of CAV systems including but not limited to car-following behavior, lane-changing, sensor performance and reliability, reaction time and wireless telecommunications (*89*).

To evaluate the strategic-level performance of large regional networks; however, using microsimulation tools is computationally intensive and may not be necessary. While macroscopic models/tools are typically used in this case observations of actual CAV systems to build these tools are not available as the technology is still in the early testing phase. Therefore, some researchers used microscopic tools to generate fundamental relationships and performance characteristics that can be used in conjunction with mesoscopic simulation-based tools at varying levels of spatial and temporal detail (*66; 120*).

The above-mentioned tools were used to evaluate different models for CAV driving behaviors such as ACC (*17; 37; 41*) and CACC (*38; 42; 49; 66*) at the facility and network levels. Some specialized tools were used to evaluate the impacts of those driving behaviors at different market penetration levels (*94; 123*). CAV-related policies and advanced traffic control algorithms were also evaluated such as dedicated AV lanes (*105*) and speed harmonization (*75-78*).

The main limitations of the existing CAV AMS tools for evaluating operational performance is 1) simplified representations of key CAV elements in performance models such as vehicle sensor performance and wireless telecommunications 2) representations available for only limited numbers of CAV system designs, without the broader collection of data needed to represent the full diversity of CAV system performance and 3) missing actual data to validate the different driving behavior interactions with other agents (pedestrians, bicyclists) in urban environments. Those gaps are discussed in further detail in the remaining of this section.

Representing the Effect of Wireless Telecommunication Networks and Information Flow on Connected and Automated Vehicle System Performance

Wireless telecommunications and information flow are two elements that are unique to CAV systems and affect their performance. CVs, for example, rely on those technologies to receive information about prevailing traffic conditions which could help increase reaction time of drivers or ease congestion through dynamic rerouting (*26*). SAVs also rely on wireless telecommunication technology to receive information about trip requests and optimal relocations.

As an integral part of the operation and performance of CAV systems, an abstract and simple representation of wireless telecommunications needs to be integrated within performance models to capture its impacts on the behavior of the new systems. One of the impacts at the individual vehicle level, for instance, is reduced reaction times of connected drivers. Those drivers would be more aware of the prevailing traffic conditions by receiving this information through V2I/V2V technology. On a system level, the communication range of CAVs affects the stability of the whole traffic stream which increases at higher communication ranges (*124*).

Failing to integrate the telecommunication aspect in performance models can affect the evaluation accuracy of CAV impacts. In the case of evaluating connected traffic stability, for example, failing to capture the information flow between vehicles or the infrastructure can lead to overestimating traffic stability. This is because it would not account for the system's capability to deliver all the messages broadcasted by the vehicles or traffic management centers (TMC) and the delays to send/receive those messages. It also would not account for other information flow limitations such as data processing, storage, and analysis.

This gap is considered a "component-level" gap as it mainly relates to the Operational Performance component of the envisioned CAV AMS system. It is also a "methodological" gap since it is a key element of CAV systems that is missing from almost all exiting CAV AMS tools. The gap is prioritized as "important" as it directly impacts the driving behavior and operations of CAV systems but is less critical than other gaps such as the lack of actual data to calibrate the behavior of emerging systems.

Potential Ways to Address this Gap

One potential way to address this gap is to integrate a communication network simulator within the operational performance component of CAV AMS system. In fact, this part of the vision for a comprehensive CAV AMS system, as discussed in task 3 (*5; 6*) This way, different information routing protocols, including topology-based (ad-hoc) protocols (*86-89*) and position-based (cluster) protocols (*48; 90-92*), can be tested within the CAV AMS system and their impacts on the performance of CAV systems can be evaluated.

The Node Mobility Model (ns-3) is an example of a communication network simulator that provides several native mobility models. It has also been integrated within the CAV simulation platform developed by Talebpour et al. (*96*). However, this simulator only incorporates MANET specific routing protocols which have limited capability in representing the dynamic information routing between vehicles and therefore may result in poor routing performance and low throughput (*89*).

Representing Sensor Performance and Reliability Aspects that Influence Vehicle Performance

As in the case of wireless telecommunication, the sensor performance and reliability aspect is a key element of CAV systems that directly affect their performance (*26*). This is more critical in the case of AVs as they rely almost exclusively on those sensors for environment perception and maneuvering (longitudinal and lateral). For example, an AV needs to estimate the distance to front vehicles and their speed so that the AV can accelerate/decelerate safely. An AV also needs to detect surrounding vehicles to be able to change lanes safely and efficiently.

Despite the integral role sensor reliability plays in CAV performance, a representation of it is missing in almost all existing CAV AMS capabilities. Those tools typically assume perfect operating conditions where sensors are fully reliable. This an unrealistic assumption since sensor performance degrades under certain conditions such as in the case of severe weather conditions (low visibility, reflective road) or in the case of a sensor damage or malfunction.

The sub-optimal sensor operating scenarios can negatively impact the driving behavior of CAV systems and therefore needs to be captured in CAV AMS systems. For example, the lower detection range of AVs under severe weather conditions can affect the speed at which those vehicles operate and safe gap they require to change lanes. Furthermore, missing sensor representation in those performance models would reduce the capability CAV AMS systems to answer important questions related to the operations of CAV systems in case of system failure and their impacts on traffic flow. For example, how would the driving behavior of an L2 AV vehicle transition to manual driving in the case of sensor failure and how would that impact the traffic flow. Would that extra reaction time create a shockwave? This is also important for answering cyber-security related questions. For example, how would the vehicle operate if the information it receives is tampered with and how would that affect the performance of the whole system?

This gap is a “component-level” gap as it is mainly related to the Operational Performance component of the envisioned CAV AMS system. It is also categorized as “methodological” since it is related to a unique characteristic of CAV systems that is missing in almost all CAV AMS capabilities. The gap is prioritized as “critical” due to its high impacts on driving behavior and the overall system performance.

Potential Ways to Address this Gap

To address this gap, sensor performance needs to be integrated within the performance models in CAV AMS systems. In car-following and lane changing models, for example, the acceleration/deceleration behavior and lane changing gap acceptance capabilities can depend on some sensor characteristics such as detection range and field of regard. Maximum or desired speeds and minimum following distances can also depend on the detection range and its reliability.

Sensor reliability can be introduced by adding a stochastic parameter to some of the sensor characteristics such as positions, speed detection, and range. The reliability can then be tuned by increasing/decreasing stochasticity in those terms; higher stochasticity means less reliable in this case. Another way to evaluate the impacts of reliability is to simulate instances of sensor failure for different automated vehicle features and assess their impacts on traffic flow.

Data toRepresenting the Differences in Driving Behaviors between Conventional Manual and Connected Vehicle Drivers

Connectivity extends drivers’ perception of their surrounding environment beyond the visual scanning of isolated drivers, potentially leading to a more responsive driving behavior (*23*). The additional information that connected drivers have access to can affect their behavior in different ways depending on the kind of information they receive. V2V communications, for instance, provides drivers with information on vehicle movement and location, such as speed and acceleration of downstream vehicles, which increases drivers' awareness of downstream traffic conditions and improves their responsiveness. V2I communications, on the other hand, provides drivers with information on road conditions, weather, TMC decisions (e.g. express lanes) which influence the drivers' strategic decisions such as route choice and departure time.

The main limitation, however, when it comes to modeling the distinct behavior of connected systems is the unavailability of actual data to validate the extent to which connectivity affects drivers’ behavior and their decisions. This limitation impedes the ability of CV models to produce reliable impact evaluations of the new driving behavior on the transportation system's performance. This is because the assumptions that may be used in CV models to capture the distinct driving behavior may be different from actual behavior.

An example of the negative impact of this gap on CAV AMS capabilities is the unreliable estimates of connected traffic flow performance capacity, stability, and safety. For example, overestimating the responsiveness of connected drivers may lead to overestimating the stability of the traffic flow as it directly relates to the reaction time of drivers (*25*). It can also overestimate the safety impacts of connected streams since it also depends on their reaction time to unexpected conditions (sudden stops, traffic congestion, etc.)

This gap is categorized as a "component-level" as it mainly relates to Operational Performance component of the envisioned CAV AMS system. It is also a "data-related" gap as previously discussed. Finally, the gap is prioritized as "critical" since it directly affects the capability of CAV AMS systems to produce validated performance impacts.

Potential Ways to Address this Gap

The best way to address this gap is by collecting actual data from field experiments on the drivers' responses/behavior in a connected environment. This is actually the main motivation of some of the USDOT funded projects such as the Connected Vehicle Pilot Program (CVPP) (*125*) and the Safety Pilot Model Deployment (SPMD) (*126*). Unfortunately, those projects only address a limited subset of the potential connected vehicle applications, so they can only shed light on driver responses to those specific applications.

The ongoing CVPP project is expected to generate an extensive data set on the behavior of connected vehicles for different V2V and V2I applications such as crash warning, intersection movement assist, speed compliance, and signalized intersections. The SPMD project, on the other hand, collected data over 2,800 vehicles equipped with V2V collision warning devices and driving in a naturalistic manner for over a year. This includes BSM messages, naturalistic, message and safety application data, and roadside equipment data. The collected data is discussed in further detail in the data source assessment document (*3*)

An alternative option to collect data on the behavior of connected vehicles can be done through driving simulators. However, the observed driving behavior in the simulator might be different from actual behavior in the field, which limits the usability of the data set.

Data to Support the Developing Vehicle-following and Lane-changing Models for Diverse Isolated-automated Vehicle Systems

A large variety of automation systems, both isolated and cooperative, are under development and will have to be represented by the envisioned CAV AMS system. The driving behavior of those systems highly depends on their level of automation and degree of coordination (cooperation). The level of automation defines which roles are performed by the automation system and which roles are performed by humans. The degree of coordination defines whether the AV system is operating in isolation or if it relies on V2V/V2I/V2X technology to coordinate with other vehicles or receive information about traffic conditions or other agents (pedestrians, bicyclists, etc.)

The driving behavior of AV systems is fundamentally different from human-driven vehicles. It heavily depends on the equipped sensors and the control algorithms installed by car manufacturers in addition to the additional information that can be received through connectivity (*26; 123; 127*). While many studies modeled the behavior of different AV systems such as ACC (*17; 37; 41*) and CACC (*38; 42; 49; 66*), their main limitation is the lack of actual data to validate the distinct vehicle-following and lane-changing behavior of AV systems.

Using actual data to calibrate driving models is important to estimate meaningful and representative behavior in CAV AMS systems. It is even more important in the case of AV systems as their driving behavior is entirely new or rather still under development. The risk of using uncalibrated parameters in AV vehicle-following and lane-changing models can be high in terms of misrepresenting the actual driving behavior of AV systems and their impacts on the performance of transportation systems. For example, increased road capacity is one of the expected impacts of the AV systems due to driving at higher traffic densities. Using uncalibrated data in this case, however, may overestimate/underestimate the actual impact on capacity. The same risk applies to estimating the traffic stability impacts which depends on the responsiveness of vehicles. Using uncalibrated models may overestimate the responsiveness of AV systems and therefore overestimate the capacity of the traffic stream. This also applies to the road safety impacts of AV systems.

In addition to misevaluating flow performance impacts, using uncalibrated AV models can misrepresent the heterogeneous traffic interactions in mixed traffic streams (isolated-manual, connected-manual, isolated-automated, connected-automated). For example, the safety distance required for AV systems to change lanes may be different from the actual distance required by those systems and therefore the number of lane changes and their impact on traffic stability may not be representative. This is particularly important for complex weaving sections with limited access/egress points such as dedicated AV lanes. More data is required to validate the merging behavior of vehicles in those sections. For example, how would AVs join the dedicated lane which has shorter than normal gaps between vehicles as they drive at high densities?

Developing validated AV driving models is not only important for the Operational Performance component of the envisioned CAV AMS system, but also important for the Supply and Demand components. As previously discussed in this Chapter, the performance of those systems directly impacts the activity patterns at the network level as well as the operation of emerging mobility options such as SAVs.

This gap is considered a “component-level” gap as it is mainly related to the operational performance component of the envisioned CAV AMS system. It is also a “data-related” gap since it involves the lack of data to validate AV models rather than the methodology to develop them. Finally, the gap is prioritized as “critical” as it directly affects the representativeness of AV driving behavior and their strategic and operational impacts.

Potential Ways to Address this Gap

Addressing this gap requires collecting more data on the driving behavior of AV systems in actual traffic conditions. For partially automated systems, data needs to be collected on the behavior of diverse assisted-driving systems such as ACC or CACC, to determine how widely their performance differs from each other and to be able to model the interactions between the diverse systems. Data is needed on the drivers’ responses when their vehicle transitions from automated driving to manual driving. This is actually the motivation of one USDOT’s projects that investigated how operators interact with partial automation under Levels 2 and 3. The “Human Factors Evaluation of Level 2 and Level 3 Automated Driving Concepts” project (*128*) collected operator behavior data such as the time to react, the time to regain control, time to activate automation, the operator's performance. More details on the data collected can be found in the referenced report, which covers early generation driving assistance systems, whose driver interfaces may not be as effective as later generation systems. An alternative option to collect data on the human’s responses during partial automation transition can be done through driving simulators. However, the data collected through those simulators are not as reliable as actual field experiments.

Collecting data for highly/fully automated vehicles is more challenging than partially automated vehicles which are already available in the market. Some prototypes can be used to collect initial data, however, most of these are usually used in controlled environments that are different from actual traffic conditions and they are tested by highly-trained test drivers rather than “typical” drivers. Some major companies have been testing AV systems in the field but those are very protective of their own data, and they are also not driven by “typical” drivers.

Data to Support Modeling the Interactions of Connected and Automated Vehicles with Vulnerable Road Users in Urban Environments

The interactions of CAV systems with vulnerable road users (VRUs), mainly pedestrians and bicyclists, in urban environments are different from road vehicle-to-vehicle interactions in multiple ways. For instance, detecting and identifying pedestrians and bicyclists at intersections is a more demanding process than identifying vehicles as it involves a much more complicated environment; signs, animals, buildings, traffic lights, etc. In addition, the actions of pedestrians and bicyclists are less predictable than those of vehicles which can make the control process of CAVs more complicated. Furthermore, the pedestrians’ safety perception of AVs specifically can be different from human-driven vehicles. For example, an AV could be perceived as a safer and more responsive vehicle, which may encourage a riskier behavior of pedestrians crossing streets in front of an AV knowing that the vehicle will likely stop safely. On the other hand, pedestrians and bicyclists normally use eye contact with the vehicle driver to determine how to interact with conventional drivers, but this option will not be available with highly automated vehicles, introducing a large uncertainty into the kind of interactions that are likely to occur.

The integration of the aforementioned interactions within CAV AMS systems is important for an accurate estimation of their performance impacts in urban settings. Intersections can be the bottlenecks for the overall system performance improvements expected by CAV systems. Despite their importance, those unique interactions with vulnerable road users are missing from existing CAV AMS capabilities. This is mainly due to the lack of data to represent movements of pedestrians and bicyclists in urban environments and of the ways in which they will interact with CAVs at a level of fidelity sufficient to support modeling their interactions with CAVs.

Failing to address this gap will affect the capability of CAV AMS systems to answer critical questions that are related to the operation of CAVs in urban environments and their impacts. For example, the AMS capability will not be able to estimate the impact of the pedestrians' safety perceptions of CAVs on intersection capacity. The riskier behavior of pedestrians with respect to CAVs may cause disruptions to the traffic flow and lower its performance. The safety implications of CAV operation at intersections is another aspect that CAV AMS systems will not be able to assess without integrating the above-mentioned interactions. For example, will CAVs cause fewer accidents at intersections?

This gap is considered a “component-level” gap as it mainly relates to the Operational Performance component of the envisioned CAV AMS system. It is also “data-related” as discussed above. The gap is prioritized as “critical” since it directly affects the performance impacts evaluated by the CAV AMS system and would help answer critical questions regarding the operations of CAV systems in urban settings—a potentially significant impediment to widespread deployment of the technologies.

Potential Ways to Address this Gap

One way to address this is to conduct real-life experiments where pedestrians/bicyclists behavior is observed at intersections while interacting with CAV systems. As testing the safety of those vehicles is still undergoing, the opportunities for conducting such experiments may be limited. To ensure the safety of operating AVs within the vicinity of pedestrians and bicyclists, they can be equipped with safety systems that can override their automatic controls in case of an emergency, such as having a driver inside the vehicle or stopping it remotely.

The Researchlab Automated Driving Delft (RADD) on the TU Delft Campus (*129*) is an example of a physical space where real-life experiments can be conducted on interactions between humans and CAV systems. One of those experiments involves driving very low speed automated shuttle buses, or WEpods as they are called by the lab, for an extended period of time on public roads with other traffic. The data collected in this experiment involved user's perceptions through face-to-face interviews, focus groups, and an online survey. More details about the experiment can be found in the referenced report (*129*).

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Integrated Network Performance

Because of the far-reaching impacts on CAVs at so many levels, as illustrated in the methodological framework discussed in Chapter 2, AMS tools by necessity entail the interaction of several different aspects and processes. To capture these interactions, model *platforms* are required, integrating various components relevant to the questions being asked. Platforms in this context are primarily conceptual analytical constructs that are embedded in a software tool. They typically entail a collection of models representing interacting agents or processes. In this case, the CAV AMS system would be a platform that integrates a collection of supply, demand, and performance models to represent the behavior of CAV systems and their impacts on transportation systems. Platforms also typically offer a foundation upon which additional capabilities may be built, albeit with varying degrees of difficulty and effort.

Existing platforms can be categorized into two main types: 1) Modeling tools for planning, intended for application at the urban and regional level; and (2) Simulation models for operations, primarily applied to facilities or urban/suburban subnetworks. Activity-Based Models (ABM) and Dynamic Traffic Assignment (DTA) procedures are both examples of advanced models on the demand and supply sides of transportation planning, respectively. While conceptually and theoretically inter-related, in practice these models have developed along essentially independent tracks (*3*).

The weak integration of the demand and supply models with CAV capability is the main limitation of existing AMS tools when it comes to evaluating the network impacts of the new system. Most of the existing CAV AMS capabilities are built as single tools to answer specific research questions such as the impacts to road capacity, mode shifts, or the operation of shared vehicles. Therefore, using those tools to evaluate the network-wide impacts of the new systems is unreliable. The remaining of the section will discuss more specific gaps regarding the above-motioned integration.

Integrating the Behavior of Different Agents in a Network Context

Evaluating the network-wide impacts of CAV systems requires capturing the interactions of different agents in a network context. Those agents include CAVs, travelers, mobility service providers, transit and network managers, freight shippers and carriers. However, as previously discussed, current AMS capabilities are built to answer questions about a specific agent on the network, and in many cases, for specific facility type. For example, some tools are built specifically to model CAVs on freeways, SAVs operations on a hypothetical network, or pedestrian movements at intersections.

Using these tools separately may misrepresent the actual impacts of CAV systems on a network level. An example of that is evaluating the expected traffic performance impacts of CAV systems. It has been shown in previous studies that CAVs would have significant improvements in throughput on freeways by moving at high speeds and densities. However, those improvements are not expected for intersection performance which means that those could become bottlenecks that would reduce the overall performance impacts of CAVs. Therefore, for a representative evaluation of the network performance, the modeling of CAVs as well as other agents at intersections need to be integrated. Another example this gap's impact is to produce inaccurate mode shifts that are caused by CAV systems. This can occur when the performance of the different modes is evaluated separately which may differ from real-life situations where those modes operate on the same network and affect each other's performances.

This gap is at the "platform level" as it relates to all the components of the envisioned CAV AMS framework. The gap is "implementation-related" as it involves the integration of different components within the CAV AMS system rather than the development of a specific component. The gap is prioritized as "critical" since integrating the behavior of different agents is essential to capture actual impacts of CAV systems.

Potential Ways to Address this Gap

To address this gap, different agents need to be modeled simultaneously within the CAV AMS system. Those would include CAVs, travelers, mobility service providers, transit and network managers, freight shippers and carriers. Modeling capabilities for each type of agents already exist. The challenge would be to integrate those within the same network context.

Integrating Demand, Supply, and Operational Performance Components

As noted earlier in the discussion, the implications of CAV technology are far reaching on multiple, yet interdependent levels (*26*). On the supply side, the technology is expected to support entirely new modes of mobility such as SAVs or hybrid transit systems. On the demand level, the availability of new mobility forms in addition to the improvements to current transportation systems through connectivity can affect the activity patterns and mobility choices of travelers. Finally, changes to both supply and demand in addition to the improvements brought by connectivity and automation to traffic flow ultimately affect the operational performance of transportation systems.

The main limitation of the existing CAV AMS capabilities is that they do not capture the interdependencies of CAV impacts on supply, demand, and operation levels. As mentioned earlier in the section, existing AMS tools are usually built to evaluate CAV impacts at a specific level only. For example, some microsimulation tools are developed to evaluate the traffic performance impacts of CAV at different market penetration levels without taking into consideration the dynamic changes in demand. Other demand models were only built to evaluate the potential mode shifts caused by CAV systems without considering the dynamic changes in performance at different demand levels.

Failing to capture the interrelations between the aforementioned components can affect the assessment reliability of the expected impacts produced by the CAV AMS system. On the demand level, for example, the shift in activity patterns of individuals/households is directly related to the performance characteristics of CAV systems. Therefore, evaluating the potential shifts in trip sequence, departure, and arrival time without taking into consideration the dynamic performance of those systems may overestimate/underestimate those potential shifts. Similarly, on the supply level, estimating traffic assignment without considering the potential activity shifts caused by CAV systems may produce inaccurate assignments and network performance impacts.

This gap is considered a “platform-level” gap, as it related to all components in the envisioned CAV AMS system. It is also an “implementation-related” gap as it involves the integration of three separate components of the CAV AMS system. Finally, the gap is prioritized as “critical” since addressing this gap is essential for a representative estimation of the network impacts of CAV systems.

Potential Ways to Address this Gap

To address this gap, the inputs/outputs of the demand, supply, and operation components need to be exchangeable within an integrated CAV AMS system. The following steps are an example of that integration:

- Integrating infrastructure representation and data generated from supply models with demand and performance models
- Integrating traffic flow patterns generated from the demand models in performance models to evaluate their network performance impacts
- Integrating operational performance of CAV systems in demand models to evaluate their impacts on activity patterns

An example of an integrated AMS system is the ABM-DTA multimodal platform developed for the Chicago Metropolitan Agency for Planning represents one of the more advanced state-of-the-art platforms developed for practical applications. It combines the CT-Ramp ABM, with an enhanced version of DYNASMART-P in combination with a fine-grained multimodal transit assignment procedure, NU-TRANS. While it is not directly CAV-capable, it represents one of the more advanced successful integrated platforms for strategic planning applications (*119*)

Chapter 8. Addressing Identified Gaps Through the Methodological Connected and Automated Vehicle Analysis, Modeling, and Simulation Framework

The comprehensive framework introduced in in this report addresses the identified gaps, summarized in Table 18, in different ways. For methodological gaps, the missing CAV related features such as sensor reliability and the multitasking effect on trip-making behavior were integrated into the different components of the framework. Data-related gaps mainly require conducting field studies, test track experiments, or driving simulations to collect data on the behavior of CAV systems. Therefore, the framework of the CAV AMS system allows the different models integrated into it to be updated whenever more data is available. Finally, implementation gaps were addressed by integrating the demand, supply, and operational performance models into a comprehensive framework of a CAV AMS platform. The remaining of this chapter briefly discusses those gaps and how they were addressed in the general framework.

Table 18. Summary of gaps identified in task 7.

Framework Component	ID	Gap Description	Level	Type	Priority
Demand Changes	DC-G1	Data describing the unique characteristics of CAV systems as a new option in demand models/components	Component	Data-related	Critical
	DC-G2	Integrating the multitasking feature of automated vehicles in demand models/components	Component	Methodological	Critical
	DC-G3	Data describing the impacts of a robotic "Chauffeur" on household activity prioritization and sequencing	Component	Data-related	Critical
Supply Changes	SC-G1	Predicting the emergence of new mobility options enabled by CAV systems and their characteristics such as SAV or hybrid systems	Component	Methodological	Desired
	SC-G2	Data describing the unique characteristics of CAV systems integrated into fleet management modeling of SAVs	Component	Data-related	Important
	SC-G3	Incorporating wireless telecommunication in infrastructure representation (V2V/V2I/V2X)	Platform	Methodological	Important
Operational Performance	OP-G1	Practical and simplified representation of the effect of wireless telecommunication networks and information flow on performance of CAV systems	Component	Methodological	Important
	OP-G2	Practical and simplified representation of sensor performance and reliability aspects that directly influence vehicle performance	Component	Methodological	Critical
	OP-G3	Data to represent the differences in driving behaviors between conventional manual drivers and connected drivers	Component	Data-related	Critical
	OP-G4	Data to support the development of vehicle-following and lane changing models for diverse AV systems	Component	Data-related	Critical
	OP-G5	Data to support modeling the interactions of CAVs with vulnerable road users (VRUs) in urban environments	Component	Data-related	Critical
Network Integration	NI-G1	Integrating the behavior of different agents in a network context	Platform	Implementation	Critical
	NI-G2	Integrating the demand, supply, and operational performance components in a comprehensive CAV AMS system	Platform	Implementation	Critical

Source: FHWA 2018

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Demand Changes

Researchers have mainly used two types of complementary tools (*115*) for evaluating the demand impacts discussed in Chapter 0: travel demand models (*83; 85*) and agent-based simulation approaches (*53; 54; 56; 81*). Demand models (including mode choice and activity-based models) use current travel behavior, demographics, employment, and modes to project future demand patterns. Since actual travel data using CAVs is not yet available, CAV studies using these models rely on a number of assumptions regarding the characteristics of CAVs, and the relative magnitudes of travelers' preferential weights associated with these characteristics. Agent-based simulation approaches have been elaborated to answer specific research questions regarding CAV impacts through interactions amongst various agents. While the interaction rules in those tools are usually based on actual behavior, the rules related to CAVs are usually assumed, or they may be based on limited field tests.

The above-mentioned tools help answer some of the main questions related to the demand changes that are expected with the deployment of the new technology. Those include questions related to the adoption of the new technology (*27; 28; 35; 81; 130*), travel mode shifts (*34; 36; 83*), vehicle ownership (*52-55*), and VMT impacts (*27; 31-33; 54; 55; 64; 83; 85*). Those tools, however, suffer from major limitations with respect to 1) the lack of data on the unique characteristics of CAVs and 2) the explicit integration and validation of the multitasking potential of AVs in those capabilities. Those limitations are discussed further below.

Describing Unique Characteristics of Connected and Automated Vehicle Systems as a New Option in Demand Models

The lack of data on the unique characteristics of CAV systems as a new mode is one of the main limitations of existing demand models. While those characteristics are typically integrated into existing CAV AMS capabilities, as well as the framework of the CAV AMS system introduced in this report, the extent to which those characteristics affect the different tuning parameters in the tools is usually assumed and not based on actual data. This will adversely affect the accuracy of the impact evaluation results.

While acquiring data requires performing field studies using CAV prototypes or commercial systems with adaptive cruise control, for example, the CAV AMS system should be designed and built with the capability to update/calibrate the different demand models in it with new data as they become available. This is an essential requirement of the envisioned CAV AMS system.

Integrating the Multitasking Feature of Automated Vehicles in Demand Models

Integrating the multitasking feature of AV in demand models is the second major limitation of existing AMS capabilities. Multitasking is maybe the most important characteristic of highly automated vehicles, with potentially the highest impact on the activity pattern shifts. Travelers would no longer be constrained by the unproductive time spent in their personal vehicles. On the contrary, users of AVs would have access to an entirely new feature in the form of an automated "Chauffeur" that may change the whole prioritization/sequence of their activities (*26*). Addressing this gap requires explicit integration of the multitasking feature into demand component of the CAV AMS systems. This feature would affect the activity patterns of the demand component as well as travel choices, see Figure 5.

Describing the Impacts of a Robotic "Chauffeur" on Household Activity Prioritization and Sequencing

As mentioned in the previous gap, the multitasking potential of highly automated vehicles will enable an entirely new transport feature in the form of an automated “chauffeur” (*5; 26*). This new form of mobility allows easier sharing of vehicles at households and can be used as an extra resource to help with family tasks around the household. For example, an AV can be used to drive one household member to their work and come back to pick up another after or an AV can be used to drop off kids at their schools. All of these new scenarios that are enabled by the new technology requires an entirely different modeling approach to capture their impacts on household activities.

In addition to methodologically integrating the new multitasking (or automated chauffeur) feature in demand models/components, as discussed in the previous gap, it is equally essential to collect data to validate the impacts of the new feature on household activity patterns or shift. The automated chauffeur feature enables numerous scenarios where household members can utilize it to maximize their productivity or convenience. However, the extent to which those scenarios will apply is unknown. Therefore, the household interaction rules and their travel decision-making process in the envisioned CAV AMS system should be updateable as new data on these interactions become available either through stated preference surveys in the short term or observed behavior in the long term.

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Supply Changes

The major supply changes associated with the deployment of CAV systems include the emergence of new mobility options and infrastructure upgrading with wireless telecommunications. While predicting the emergence of new modes is beyond the capability of any tool, most researchers built special purpose tools to model the operations of CAV enabled mobility options such as SAVs (*54; 56; 60; 61*). As for infrastructure changes, most tools lacked the incorporation of wireless telecommunication in their systems configurations which is an essential feature of CAV systems. The remaining of this section discusses how the CAV AMS framework addresses those main gaps.

Predicting New Mobility Options Enabled by Connected and Automated Vehicle Systems and Their Characteristics

As mentioned earlier, the rapid development in wireless telecommunication technologies and the high adoption rate of those technologies have enabled radically new forms of mobility and opportunities for multi-mode integrations that were not possible or thought of less than 20 years ago. Predicting those changes, however, is beyond of capability of any analysis tool. It would rather require transport planners and decision makers to follow the trends in technological advancements and use their professional judgment.

To reduce the uncertainty surrounding the operation and behavior of new mobility systems, the supply changes component of the CAV AMS framework defines operational scenarios of the new modes based on current and predicted market trends, technology development, regulations, and ultimately expert judgment. Those scenarios will determine the range of likely operational characteristics of new modes and the type of telecommunication technology in place (V2I, V2V, or V2X).

Describing the Unique Characteristics of Connected and Automated Vehicle Systems Integrated into Fleet Management Modeling

The operation of SAV fleets has been the focus of many researchers as one of most anticipated new modes of travel. One of the major limitations of current simulation tools modeling the operations of SAV fleets is the lack of actual data describing the characteristics of anticipated AVs, such as costs, and relying on multiple assumptions regarding those characteristics. As in the case of other data-related gaps, the interaction rules within SAV management models in the CAV AMS framework should be updateable as new information becomes available regarding SAV fleets.

Incorporating Wireless Telecommunication in Infrastructure Representation (V2V/V2I/V2X)

As mentioned in the previous chapter, wireless telecommunication is missing from the representation of current modeling tools despite its integral role in the operation and behavior of CAV systems. Therefore, the envisioned CAV AMS system integrates a setup of wireless telecommunication coverage within the network representation of the supply component. Depending on the type of wireless telecommunication technology used, this representation can be in the form of nodes/links with communication ranges or areas of coverage.

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Operational Performance

To evaluate the performance impacts of CAV systems, researchers have mainly used microsimulation tools which offer the highest fidelity to comprehensively capture the characteristics of CAV systems including but not limited to car-following behavior, lane-changing, sensor detection capabilities, reaction time and wireless telecommunications (*89*). To evaluate the strategic-level performance of large regional networks; however, researchers used microscopic tools to generate fundamental relationships and performance characteristics that can be used in conjunction with mesoscopic simulation-based tools at varying levels of spatial and temporal detail (*66; 120*).

The above-mentioned tools were used to evaluate different models for CAV driving behaviors such as ACC (*17; 37; 41*) and CACC (*38; 42; 49; 66*) at the facility and network levels. Some specialized tools were used to evaluate the impacts of those driving behaviors at different market penetration levels (*94; 123*). CAV-related policies and advanced traffic control algorithms were also evaluated such as dedicated AV lanes (*105*) and speed harmonization (*75-78*).

The main limitations of the existing CAV AMS tools for evaluating operational performance is 1) missing representation of key CAV elements in performance models such as vehicle sensor performance and wireless telecommunications and 2) missing actual data to validate the different driving behavior of new systems and their interactions with other agents (pedestrians, bicyclists) in urban environments. Those gaps are discussed in further detail in the remaining of this section.

Representating the Effect of Wireless Telecommunication Networks and Information Flow on Connected and Automated Vehicle Performance

The lack of abstract representation of wireless telecommunications and their impacts on connected driving behavior is one of the main gaps in existing microsimulation tools. As an integral part of the operation and performance of CAV systems, an abstract and simple representation of wireless telecommunications needs to be integrated within performance models to capture its impacts on the behavior of the new systems. One of the impacts at the individual vehicle level, for instance, is reduced reaction times of connected drivers. Those drivers would be more aware of the prevailing traffic conditions by receiving this information through V2I/V2V technology. On a system level, the communication range of CAVs affects the stability of the whole traffic stream which increases at higher communication ranges (*124*).

The comprehensive framework of the envisioned CAV AMS system addresses this limitation by integrating wireless telecommunication and information flow into the modeling framework for evaluating operational performance, see Figure 4. Through this integration, different information routing protocols, including topology-based (ad-hoc) protocols (*86-89*) and position-based (cluster) protocols (*48; 90-92*), can be tested within the CAV AMS system and their impacts on the performance of CAV systems can be evaluated.

Representing Sensor Performance Aspects that Influence Vehicle Performance

Sensor performance is another unique feature of CAV systems (*26*) that is missing from existing CAV AMS capabilities. Those tools typically assume perfect operating conditions where sensors are fully accurate. This an unrealistic assumption since sensor performance degrades under certain conditions such as in the case of severe weather conditions (low visibility, reflective road) or in the case of a sensor damage or malfunction. This is more critical in the case of AVs as they rely on those sensors for environment perception and maneuvering (longitudinal and lateral).

To address this gap, the proposed CAV AMS framework integrates sensor capabilities within operational performance models in the system. In car-following models, for example, the acceleration/deceleration behavior can depend on some sensor characteristics such as detection range. At higher detection ranges, CAVs can respond earlier and more gently to slower traffic ahead since vehicles would have more complete information about their surrounding environment. Maximum or desired speeds can also depend on the detection range. Sensor performance variability can be introduced by adding a stochastic parameter to some of the sensor characteristics such as field of regard and accuracy of speed and range detection.

Representing the Differences in Driving Behaviors between Manual and Connected Drivers

Connectivity extends drivers' perception of their surrounding environment beyond the visual scanning of isolated drivers, leading to a more responsive driving behavior (*23*). The main limitation, however, when it comes to modeling the distinct behavior of connected systems is the unavailability of actual data to validate the extent to which connectivity affects drivers' behavior and their decisions. This limitation would have severely impacted the ability of CV models to produce reliable impact evaluations of the new driving behavior on the transportation system's performance. This is because the assumptions that may be used in CV models to capture the distinct driving behavior may be different from actual behavior. While addressing the lack of data requires collecting more data on the behavior of connected drivers, the proposed CAV AMS system would have the capability to calibrate/replace the driving behavior models within the operational performance component as new data becomes available.

Supporting Development of Vehicle-following and Lane-changing Models

A great diversity of automation systems, both isolated and cooperative, are under development and will have to be represented by the envisioned CAV AMS system. The driving behavior of those systems is fundamentally different from human-driven vehicles. It heavily depends on the equipped sensors and the control algorithms installed by car manufacturers in addition to the additional information that can be received through connectivity (*26; 123; 127*). While many studies modeled the behavior of different AV systems such as ACC (*17; 37; 41*) and CACC (*38; 42; 49; 66*), their main limitation is the shortage of actual data to validate the distinct vehicle-following and lane-changing behavior of AV systems. Therefore, as in the case of connected driving behavior, the AV driving models in the envisioned CAV AMS system can be calibrated/replaced with new data on the behavior of AVs at it becomes available.

Modeling the Interactions of Connected and Automated Vehicles with Vulnerable Road Users in Urban Environments

The interactions of CAV systems with vulnerable road users (VRUs), mainly pedestrians and bicyclists, in urban environments are different from road vehicle-to-vehicle interactions in multiple ways. For instance, detecting and identifying pedestrians and bicyclists at intersections is a more demanding process than identifying vehicles as it involves a much more complicated environment; signs, animals, buildings, traffic lights, etc. The integration of the aforementioned interactions within existing CAV AMS capabilities is often missing due to the lack of data to represent movements of pedestrians and bicyclists in urban environments at a level of fidelity sufficient to support modeling their interactions with CAVs. To that end, the proposed CAV AMS system should be able to integrate those interactions within the operational performance component when new data on VRUs are collected.

Gaps in Existing Connected and Automated Vehicle Analysis, Modeling, and Simulation Capabilities for Evaluating Integrated Network Performance

To understand the overall impacts of CAV system, it is necessary to capture the interactions of the different processes and aspects related to those systems at a network level. Existing CAV AMS tools mostly focus on specific research questions related to CAV systems, such their impacts on traffic flow or mode choice, therefore, missing the relationships between those elements (for example how the travel time simulated affects mode choice). In other words, the main limitation of existing AMS capabilities with regard to evaluating the network-level impacts of CAV systems is the weak integration of the demand, supply, and performance models. Those are further discussed below.

Integrating the Behaviors of Different Agents in a Network Context

Evaluating the network-wide impacts of CAV systems requires capturing the interactions of different agents in a network context. Those agents include CAVs, travelers, mobility service providers, transit and network managers, freight shippers and carriers. However, as previously discussed, current AMS capabilities are built to answer questions about a specific agent on the network, and in many cases, for specific facility type. For example, some tools are built specifically to model CAVs on freeways, SAVs operations on a hypothetical network, or pedestrian movements at intersections. To address this gap, the proposed CAV AMS framework models the interactions of those different agents within an integrated platform. For example, the interactions between different modes in the demand component or simulating the operations of SAV fleets in mixed traffic.

Integrating the Demand, Supply, and Operational Performance Components in a Connected and Automated Vehicle Analysis, Modeling, and Simulation System

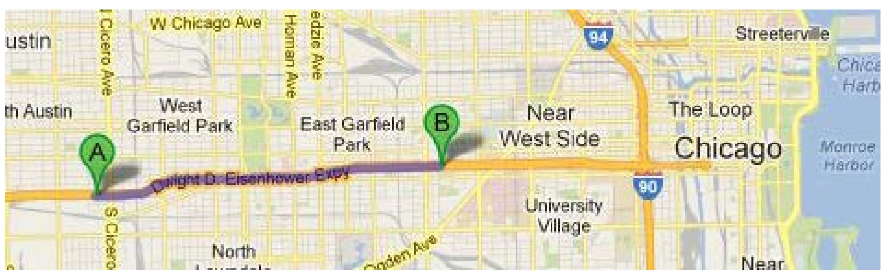
As noted earlier in the discussion, the implications of CAV technology are far reaching on multiple, yet interdependent levels (*26*). On the supply side, the technology is expected to support entirely new modes of mobility such as SAVs or hybrid transit systems. On the demand level, the availability of new mobility forms in addition to the improvements to current transportation systems through connectivity can affect the activity patterns and mobility choices of travelers. Finally, changes to both supply and demand in addition to the improvements brought by connectivity and automation to traffic flow ultimately affect the operational performance of transportation systems.

The main limitation of the existing CAV AMS capabilities is that they do not capture the interdependencies of CAV impacts on supply, demand, and operation levels. To address the gap, the CAV AMS framework was built to integrate the aforementioned components into a full platform where the feedback of one component affects the output of another, see Figure 1. For example, one of the major factors that affect mode choice, in demand models, is travel time. In this framework, the operational performance component would simulate the operations of CAV systems on a network and feed dynamic travel times resulting from those simulations into the demand component to evaluate the impacts of CAV systems on mode choice.

Chapter 9. Project Case Study – Selected Testbed

The objective of this case study is to conduct a proof-of-concept test of a prototype CAV AMS framework as discussed in the case study plan (*131*). The selected case study focuses on the operational performance impacts of CAV systems in a mixed traffic environment (i.e, CAVs and human drivers) at different market penetrations of the technology. To do so, the study uses an integrated traffic-telecommunication microsimulation tool that was developed at Northwestern University as a testbed. This chapter provides a description of the microsimulation tool and the modeling framework.

The microsimulation platform is a special-purpose tool for simulating mixed traffic conditions on freeways in a connected environment. The platform integrates three different driving behaviors: regular vehicles, connected vehicles, and automated vehicles (connected and isolated) in addition to modeling V2I/V2V wireless telecommunications. The testbed uses a 3.5-mile section of I-290 in Chicago, Illinois (illustrated below). The remainder of this chapter discusses the modeling framework embedded in this platform.



Original Photo: © 2018 Google ®

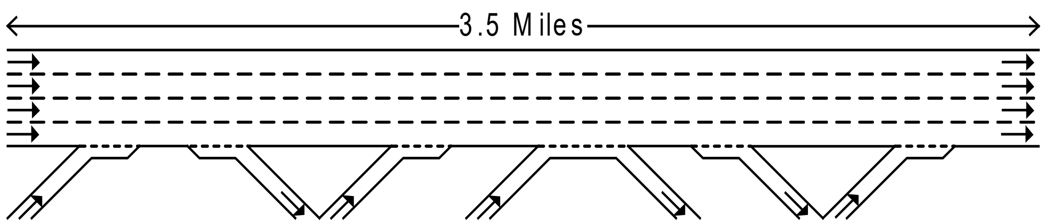


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Figure 12. I-290E study segment in Chicago, IL.

Acceleration (Car Following) Framework

The acceleration framework recognizes the differences in the longitudinal behavior of four distinct driving behaviors:

1. Isolated-manual (regular human).
2. Connected-manual (connected human).
3. Isolated-automated (isolated robot).
4. Connected-automated (connected robot).

Isolated-Manual Vehicles

Modeling isolated-manual (regular) vehicles relies on the acceleration model posited by Hamdar et al. (132), which is based on Kahneman and Tversky's prospect theory, as extended by Talebpour et al. (96) to capture drivers' different behaviors in congested versus uncongested regimes. Accordingly, based on prospect theory, they introduced two value functions, one for modeling driver behavior in congested regimes and one for modeling driver behavior in uncongested regimes. The uncongested traffic value function in this model has the following form:

$$U_{PT}^{UC}(a_n) = \frac{\left[w_m + (1-w_m)\left(\tanh\left(\frac{a_n}{a_0}\right)+1\right)\right]}{2}\left[\frac{\left(\frac{a_n}{a_0}\right)}{\left(1+\left(\frac{a_n}{a_0}\right)\right)^{\left(\frac{\gamma-1}{2}\right)}}\right] \quad [1]$$

where U_{PT}^{UC} denotes the value function for the uncongested traffic conditions $\gamma > 0$, w_m are parameters to be estimated, and $a_0 = 1m/s^2$ is used to normalize the acceleration. They proposed the following value function for the congested traffic condition:

$$U_{PT}^{C}(a_n) = \frac{\left[w'_m + (1-w'_m)\left(\tanh\left(\frac{a_n}{a_0}\right)+1\right)\right]}{2}\left(\frac{a_n}{a_0}\right)^{\gamma'} \quad [2]$$

where U_{PT}^{C} denotes the value function for the congested traffic conditions. $\gamma' > 0$ and w'_m are parameters to be estimated. At each evaluation stage, based on drivers' perception of their surrounding traffic condition, drivers employ the corresponding value functions to evaluate the gains from the chosen acceleration. They introduced a binary probabilistic regime selection mechanism into the evaluation stage where drivers use the resulting utility to evaluate each acceleration value, given by:

$$U_{PT}(a_n) = P(C).U_{PT}^{C} + P(UC).U_{PT}^{UC} \quad [3]$$

where U_{PT}, $P(C)$, and $P(UC)$ denote the expected value function, the probabilities of driving in a congested traffic condition, and the probability of driving in an uncongested traffic conditions, respectively. Note that it is assumed that drivers choose the acceleration value function that gives them the higher value for the observed acceleration. Once the expected value function is calculated, the total utility function of acceleration can be formulated as follows:

$$U(a_n) = (1 - p_{n,i})U_{PT}(a_n) - p_{n,i} w_c k(v, \Delta v) \quad [4]$$

where $p_{n,i}$ denotes the crash probability. Finally, to reflect the stochastic response adopted by the drivers, the logistic functional form specified by Hamdar et al. (95) is used to calculate the probability density function:

$$f(a_n) = \begin{cases} \dfrac{e^{\beta_{PT} U(a_n)}}{\int_{a_{\min}}^{a_{\max}} e^{\beta_{PT} U(a')} da'} & a_{\min} < a_n < a_{\max} \\ 0 & Otherwise \end{cases} \quad [5]$$

where β_{PT} reflects the sensitivity of choice to the utility $U(a_n)$.

The model has been extensively tested and validated using NGSIM trajectory data and is implemented in simulations recognizing the heterogeneity in user preferences captured in the available data.

Connected-Manual Vehicles

These vehicles are expected to have the capability of sending/receiving information to/from other vehicles and infrastructure-based equipment. Assuming reliable connectivity in the vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications networks, each vehicle will receive information about other vehicles in this network. The driver also receives real-time updates about decisions made by the traffic management center (TMC); e.g., real-time changes in speed limit. However, this information may not be available at all times and locations, and drivers' behavior may change according to the amount of information they receive.

With active V2V, drivers are certain about other (connected) drivers' behaviors. They are also aware of the driving environment, road condition, and weather condition downstream of their current location. A deterministic acceleration modeling framework is suitable for modeling this environment. This tool utilizes the Intelligent Driver Model (IDM) to model this connected environment. While capturing different congestion dynamics, this model provides greater realism than most of the deterministic acceleration modeling frameworks.

IDM specifies a following vehicle's acceleration as a continuous function of the vehicle's current speed, the ratio of the current spacing to the desired spacing, and the difference between the leading and the following vehicles' velocities. Perceptive parameters such as desired acceleration, desired gap size, and comfortable deceleration are considered in this model:

$$a_{IDM}^{n}(s_n, v_n, \Delta v_n) = \overline{a}_n \left[1 - \left(\frac{v_n}{v_0^n} \right)^{\delta_n} - \left(\frac{s^*(v_n, \Delta v_n)}{s_n} \right)^2 \right] \quad [6]$$

$$s^*(v_n, \Delta v_n) = s_0^n + T_n v_n + \frac{v_n \Delta v_n}{2\sqrt{\overline{a}_n \overline{b}_n}} \quad [7]$$

where δ_n is the free accelaration exponent, T_n is the desired time gap, a_n is the maximum accelaration, b_n is the desired decelaration, s_0^n is the jam distance, and v_0^n is the desired speed. Those are parameters to be calibrated. Note that the braking term in the IDM is designed to preclude crashes in the simulation.

When V2V is not active, driving is essentially similar to that of unconnected vehicles, as no active communication exists between vehicles. In the presence of V2I communications, drivers directly receive information about TMC decisions and recommendations—for example, speed limits in the case of speed harmonization—and can thus follow it. However, their reaction times would still be sluggish like regular drivers.

Isolated-Automated Vehicles

Two key factors should be considered in modeling the car-following behavior of automated vehicles: (1) their ability to constantly monitor other vehicles in their vicinity, which can result in a deterministic behavior in dealing with other drivers' behavior; and (2) their ability to react rapidly to any changes in the driving environment. Therefore, a deterministic acceleration modeling framework is suitable for modeling the car-following behavior of automated vehicles. Considering the sensor range and accuracy limitations, Talebpour et al. (25) introduced a car-following model for automated vehicles (connected and isolated) based on the previous simulation studies by Van Arem et al. (133) and Reece and Shafer (99). They simulated individual sensors in order to create the input data for the acceleration model. Our approach assumes that all automated vehicles are equipped with similar sensors. Figure 13 illustrates the sensor formation of an automated vehicle. These sensors are (Smart Micro) Automotive Radar (UMRR-00 Type 30) with 90m±2.5 percent detection range and ±35 degrees horizontal Field of View (FOV). Each sensor updates the sensing information every 50ms and can track up to 64 objects.

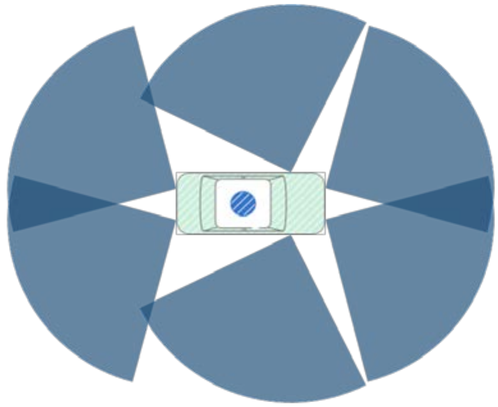

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Figure 13. Radar sensor formation on an automated vehicle.

Considering the limitations of the sensors, automated vehicles should be ready to react to any situation outside of their detection range as soon as it is spotted (e.g., a vehicle at a complete stop right outside of the sensors detection range). Moreover, if a leader is spotted, it is reasonable to assume that the speed of the automated vehicle should be low enough to allow it to stop if its leader decides to decelerate with its maximum deceleration rate and reach a full stop. Considering the maximum possible deceleration for the automated vehicle and its leader, maximum safe speed can be calculated using the following equations:

$$\Delta x_n = \left(x_{n-1} - x_n - l_{n-1}\right) + v_n \tau + \frac{v_{n-1}^2}{2a_{n-1}^{decc}} \qquad [8]$$

$$\Delta x = \min\{Sensor\ Detection\ Range, \Delta x\} \qquad [9]$$

$$v_{\max} = \sqrt{-2a_i^{decc}\Delta x} \qquad [10]$$

where n and $n\text{-}1$ represent the automated vehicle and its leader, respectively; x_n is the location of vehicle n, l_n is the length of vehicle n, v_n is the speed of vehicle n, τ is the reaction time of vehicle n, and a_n^{decc} is the maximum deceleration of vehicle n. Figure 14 illustrates the concept of maximum safe speed; any speed below the maximum safe speed curve is considered to be safe.

In addition to the safety constraint, the vehicle movement model should be considered. This study adopted the model by Van Arem et al. to calculate the acceleration of the automated vehicle at every decision point:

$$a_n^d(t) = k_a a_{n-1}(t-\tau) + k_v(v_{n-1}(t-\tau) - v_n(t-\tau)) + k_d(s_n(t-\tau) - s_{ref}) \qquad [11]$$

where a_n^d is the acceleration of vehicle i; k_a, k_v and k_d are model parameters; s_n is the spacing; and s_{ref} is the maximum between minimum distance ($s_{\min}$), following distance based on the reaction time (s_{system}), and safe following distance (s_{safe}). In this study, minimum distance is set at 2.0 m and s_{system} and s_{safe} is calculated as follows:

$$s_{safe} = \frac{v_{n-1}^2}{2}\left(\frac{1}{a_n^{decc}} - \frac{1}{a_{n-1}^{decc}}\right) \qquad [12]$$

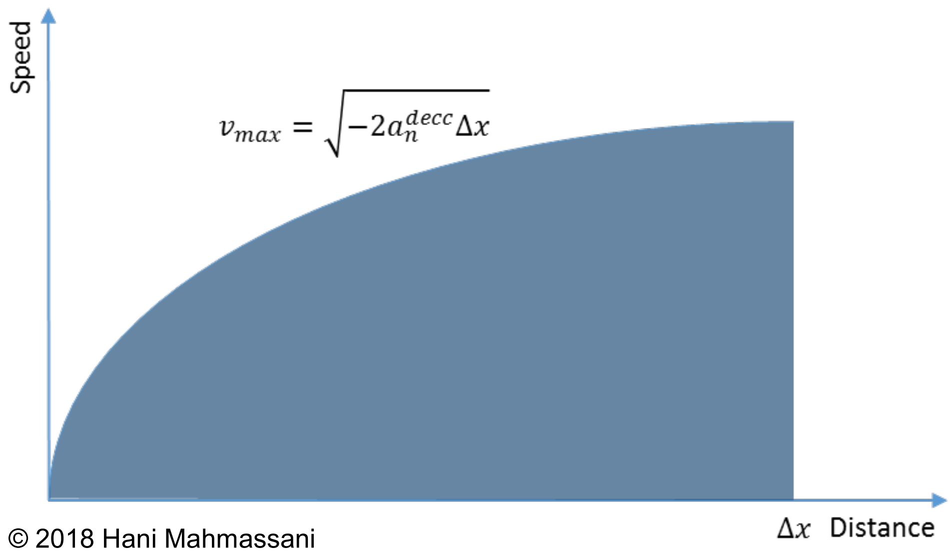

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Figure 14. Maximum safe speed curve

Finally, the acceleration of the automated vehicle can be calculated using the following equation:

$$a_n(t) = \min\left(a_n^d(t), k(v_{\max} - v_n(t)\right) \qquad [13]$$

where k is a model parameter. In this study, based on the recommendations of Arem et al. (133), k=1.0, $k_a = 1.0$, $k_v = 0.58$, and $k_d = 0.1$.

Connected Automated Vehicles

Modeling these vehicles in this framework is similar to modeling isolated-automated vehicles. However, those models assume a larger sensor range of 300m instead of 90 due to the extra information that connected vehicles can collect through wireless telecommunication (134).

Lane-changing Model

Lane changing is a cause of perturbations in multilane traffic and is especially sensitive to human error, particularly at high speeds in high-density environments. Hence, connectivity and automation are expected to enable smoother lane changes with fewer abrupt maneuvers than human-negotiated cases. The literature offers few examples to model these situations under connected and/or autonomous cases. Talebpour et al. (94) developed a game-theory-based lane-changing model that captures the dynamic interactions between drivers during discretionary and mandatory lane-changing maneuvers and introduces a game structure to model behavior when drivers are not aware of the nature of the lane-changing maneuver (i.e., mandatory vs. discretionary). They proposed two game types:

- Two-person non-zero-sum non-cooperative games under complete information to model lane-changing decisions when drivers and automated vehicles are aware of the nature of lane-changing maneuver.
- Two-person non-zero-sum non-cooperative games under incomplete information to model lane-changing decisions in the absence of such knowledge.

The target vehicle (i.e., the one that is changing lanes) is assumed to have two pure strategies (change lanes, wait) and the lag vehicle (the new follower after the lane-changing maneuver) has three pure strategies (accelerate, decelerate, and change lanes). Table 19 and Table 20 illustrate the structure of discretionary and mandatory lane-changing games, respectively.

Table 19. Discretionary lane-changing game with inactive V2V communication in normal form.

ACTION		Target Vehicle	
		A_1 **(Change Lane)**	A_2 **(Do not Change Lane)**
Lag Vehicle	B_1 **(Accelerate)**	(P_{11}, R_{11})	(P_{12}, R_{12})
	B_2 **(Decelerate)**	(P_{21}, R_{21})	(P_{22}, R_{22})
	B_3 **(Change Lane)**	(P_{31}, R_{31})	(P_{32}, R_{32})

Source: A. Talebpour, H.S. Mahmassani, F.E. Bustamante. 2016. "Modeling Driver Behavior in a Connected Environment: Integrated Microscopic Simulation of Traffic and Mobile Wireless Telecommunication Systems," *Transportation Research Record: Journal of the Transportation Research Board* 2560(1): 75-86.

Table 20. Mandatory lane-changing game with inactive V2V Communication in Normal Form. (127)

ACTION		Target Vehicle	
		A_1 (Change Lane)	A_2 (Do not Change Lane)
Lag Vehicle	B_1 (Accelerate)	(P_{11}, Q_{11})	(P_{12}, Q_{12})
	B_2 (Decelerate)	(P_{21}, Q_{21})	(P_{22}, Q_{22})
	B_3 (Change Lane)	(P_{31}, Q_{31})	(P_{32}, Q_{32})

Source: A. Talebpour, H.S. Mahmassani, F.E. Bustamante. 2016. "Modeling Driver Behavior in a Connected Environment: Integrated Microscopic Simulation of Traffic and Mobile Wireless Telecommunication Systems," *Transportation Research Record: Journal of the Transportation Research Board* 2560(1): 75-86.

When drivers or automated vehicles are uncertain about the nature of the lane-changing maneuver, Harsanyi transformation is used to transform a game of incomplete information to a game of imperfect information. This method introduces "nature" as a player—one that determines the nature of the lane-changing maneuver with a certain probability. Figure 15 illustrates the structure of the transformed game in extended form. Additional detail about the calibration and validation of these game structures can be found in Talebpour et al. (25)

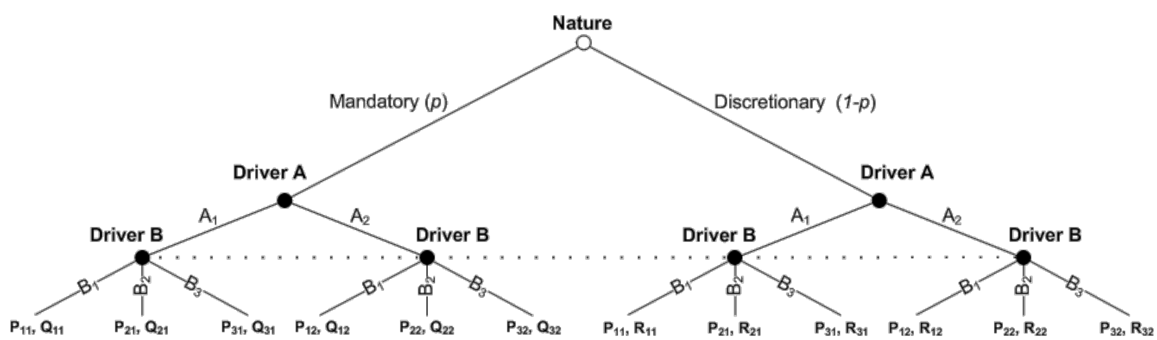


Figure 15. Lane-changing game with inactive V2V communication in extensive form.

Jointly Modeling Telecommunications Flow Aspects for Connected Vehicle Systems

In addition to the challenges associated with modeling driver behavior in a connected environment, simulating wireless communications to assess connectivity in V2V/V2I networks is essential for determining the existence of a reliable, uninterrupted flow of information, which is necessary for a reliable connected driving environment. Full connectivity in these wireless communications networks does not always exist due to several factors, including physical barriers and signal interference. Information availability plays a critical role in driver decision making. Considering the effects of information on drivers' operational, tactical, and strategic decisions, simulating the flow of information along with vehicular movements is essential for determining the information available to individual drivers while making driving-related decisions.

Accordingly, several studies have attempted to simulate the flow of information along with vehicular movements. However, most of these efforts do not capture the influence of additional information on driver behavior and vehicular movements, though there are a few exceptions. Moreover, these studies use simple acceleration and lane-changing frameworks that are not sensitive to the flow of information in V2V/V2I communications networks. For instance, Traffic and Network Simulation Framework (TraNS) is based on an integration of Simulation of Urban MObility (SUMO) and NS-2. TraNS, in its application-centric mode, provides a basic mechanism to impose certain decisions (e.g. reducing speed and changing lane) to drivers through wireless communications. However, the modeling framework in SUMO does not recognize different vehicle types (connected, automated, and regular vehicles) and it is not sensitive to the flow of information in a connected environment. Other cited examples suffer similar drawbacks.

For V2V/V2I communications networks, similar to any wireless network, one can define a link between two nodes if they communicate with each other. Let r_i and r_j denote the effective range of communication for nodes i and j, respectively. Let r_{ij} represent the Euclidean distance between nodes i and j. These two nodes can communicate with each other if $r_{ij} < r_i$ and $r_{ij} < r_j$. Let $P = P_i$ denote the transmission power at node i. Adopting the propagation-receiver model without fast-fading and shadowing effects, node j can receive information from node i if:

$$\frac{P_i / r_{ij}^{\alpha}}{noise} \geq snr \qquad [14]$$

Where snr denotes signal-to-noise ratio; α is the pass-loss parameter and is equal to 2 for free-space propagation. A similar condition is required for node j to receive information from node i. Once both of these conditions are satisfied, these two nodes can communicate with each other.

Considering Equation 9 with the above assumptions, the maximum effective range for node i can be calculated as $R_i = P_i^{1/\alpha}$. Every node that falls into this range can hear from node i. In other words, in order to communicate, both nodes should lie inside each other's effective communication range.

The above link construction process can be used in any wireless network. However, V2V and V2I communications networks, unlike most wireless networks, change dynamically over time, which makes the link construction process quite challenging. This platform adopts Network Simulator 3 (ns-3) to simulate wireless communications and to construct communication links; ns-3 is a discrete-event communications network simulator that implements the IEEE 802.11p protocol, which is is specifically designed to address the communication needs in ITS applications and is the standard protocol for V2V and V2I communications. As a result, the model uses the IEEE 802.11p protocol for dedicated short-range communications (DSRC). Two factors play important roles in simulating V2V and V2I communications networks: the information routing protocol and the node mobility model.

Performance Measures

Throughput

CAV technologies are expected to increase the flow throughput of transportation facilities by increasing flow densities. However, such impacts are dependent on the market penetration and operating characteristics of those technologies. Throughput can be quantified by measuring the number of vehicles passing through per hour and the variability of speeds within a facility segment. The fundamental diagram (flow-density) was used in this case study to measure throughput.

Stability

Flow stability refers to the traffic stream's ability to recover its steady-state properties (density-speed) after incurring a perturbation. The scatter in the traffic fundamental diagram was used as an indicator of traffic stability.

Travel Time Distribution

Travel time distribution refers to the distribution of travel times experienced by individual vehicles in the simulation. It is another indicator of traffic congestion and speed experienced by simulated drivers.

Chapter 10. Case Study Scenarios – Description and Simulation Results

Using the integrated microsimulation platform introduced in the previous chapter, three sets of scenarios were evaluated. Those scenario sets serve as a small-scale experiment using a CAV AMS prototype in addition to answering a number of research questions regarding the operations of CAV systems. The three sets evaluated below analyze the following:

- The performance of mixed traffic flow.
- The impact of AV sensor performance on mixed traffic flow.
- The impact of automated truck platooning on mixed traffic flow.

The remainder of this chapter presents the rationale, methodology, and simulation experiments for each set of scenarios.

Performance of Mixed Traffic Flow

To explore questions regarding the flow impacts of automated and connected vehicles, it is important to formulate microscopic models that capture the capabilities of the new technologies as well as the attendant behavior of human drivers. For human drivers, one could rely on a variety of existing models, albeit actual behavior will only be observed when there is sufficient deployment of these technologies. The specific logic for automated vehicles will be robotic in nature and essentially supplied by the operating entity, and thus likely proprietary. However, recent experiments on prototype vehicles provide a good idea about the expected behavior of those vehicles. Connected vehicle behavior would be largely dependent on the implemented capabilities. With the expected availability of post-deployment data, these microscopic mechanisms will likely be reviewed and improved.

Methodology

As CAV technology is expected to enter the market gradually, an essential question to researchers and policymakers is how the interactions among the different types of drivers (isolated-manual, connected-manual, isolated-automated, and connected-automated) would affect traffic flow performance in the short run at low CAV market penetration and in the long run at high market penetration. To answer that question, the four distinctive driving behaviors in the microsimulation testbed are used to simulate those interactions and evaluate their effects on traffic flow performance. The scenarios presented in this section are intended to evaluate traffic performance in mixed traffic conditions by varying the market penetration (vehicle percentage) of connected-manual, isolated-automated, and connected-automated vehicles. These scenarios attempt to answer three main research questions explored in the following section:

1) The impact of connected-manual driving on traffic flow performance.
2) The impact of isolated-automated driving on traffic performance.
3) The impact of connected-automated driving on traffic flow performance.

Results and Discussion

Impact of Connected Manual Driving on Traffic Performance

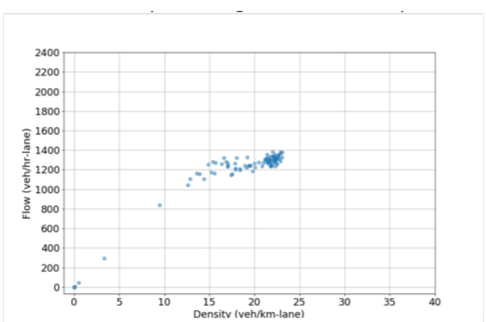
The following set of scenarios, summarized in Table 21, test the impact of connected manual driving by varying the market penetration of the connected-manual vehicles at low (30 percent), medium (60 percent), and high (90 percent) penetration rates. Automated vehicles, whether connected or isolated, were assumed to be zero in those scenarios.

Table 21. Connected-manual driving scenarios by market penetration rate (percent).

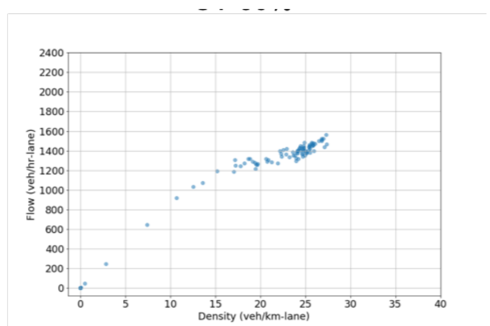
Scenario Description	Isolated-Human (RV)	Connected-Human (CV)	Isolated-Automated (AV)	Connected-Automated (CAV)
Baseline – Human	100	**0**	0	**0**
Low CV	70	**30**	0	**0**
Medium CV	40	**60**	0	**0**
High CV	10	**90**	0	**0**

Source: FHWA 2018

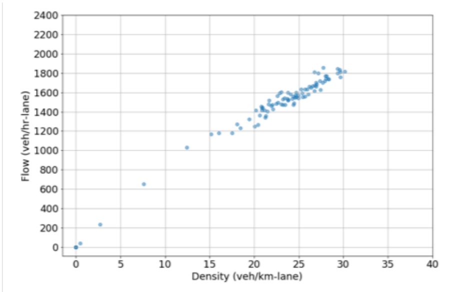
Figure 16 shows the fundamental diagrams for the four scenarios mentioned above. The results indicate that connectivity at medium to high market penetration rates (> 60 percent) can improve traffic throughput compared to the baseline case of 100 percent isolated-manual vehicles. The extra information received by connected drivers through wireless telecommunication improves their responsiveness and therefore the overall performance of traffic. Figure 17 shows the travel time distribution for the abovementioned scenarios. As seen from the figures, connectivity at low- to high- market penetration rates can also improve travel time, as seen by the shift in the distribution to the towards the lower travel time bins (left side). The improved responsiveness of connected drivers lowers the likelihood of unexpected slow-downs and overall travel time.



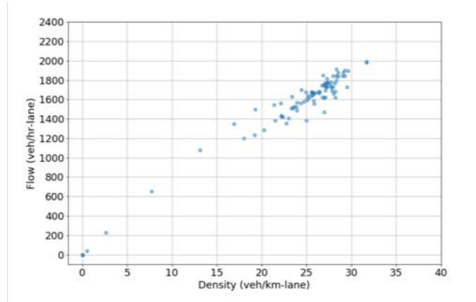
a) Base (100 percent regular vehicles).



b) Connected vehicle market penetration at 30 percent.

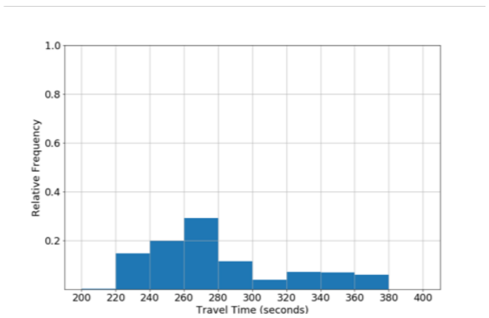


c) Connected vehicle market penetration at 60 percent.

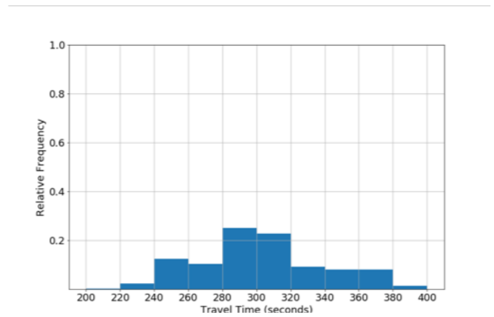


d) Connected vehicle market penetration at 90 percent.

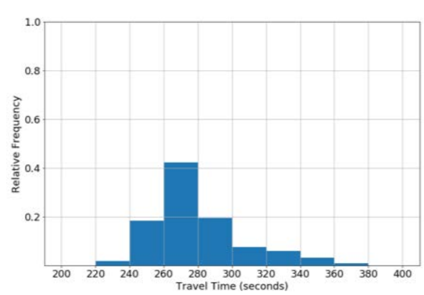
Figure 16. Fundamental diagrams for low (30 percent), medium (60 percent), and high (90 percent) connected vehicle market penetration rates.



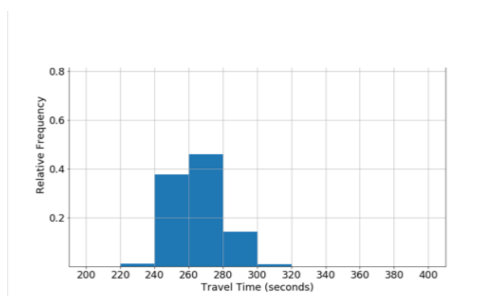
a) Base (100 percent regular vehicles).



b) Connected vehicle market penetration at 30 percent.



c) Connected vehicle market penetration at 60 percent.



d) Connected vehicle market penetration at 90 percent.

Figure 17. Travel time distributions for low, medium, and high connected vehicle market penetration rates.

Impact of Isolated Automated Driving on Traffic Performance

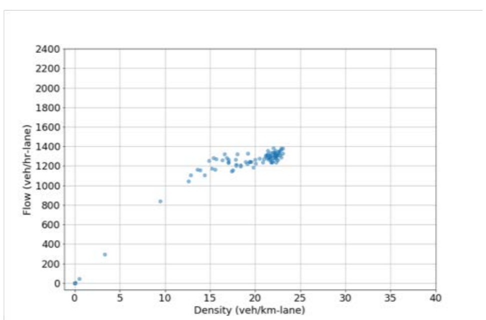
The following set of scenarios, summarized in Table 22, evaluates the impact of isolated-automated driving behavior on traffic performance. Isolated-automated refers to automated vehicles that rely solely on their sensors for environment perceptions and driving logic without receiving any information from surrounding connected vehicles. The scenarios test traffic performance (throughput and travel time) at three automation market penetration rates: low (30 percent), medium (60 percent), and high (90 percent) as seen in the following figures.

Table 22. Isolated automated driving scenarios by market penetration rate (percent).

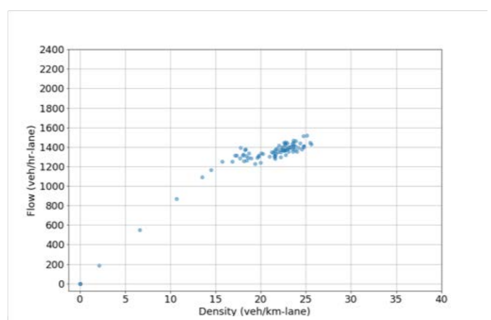
Scenario Description	Isolated-Human (RV)	Connected-Human (CV)	Isolated-Automated (AV)	Connected-Automated (CAV)
Baseline – Human	**100**	0	**0**	0
Low AV	**70**	0	**30**	0
Medium AV	**40**	0	**60**	0
High AV	**10**	0	**90**	0

Source: FHWA 2018

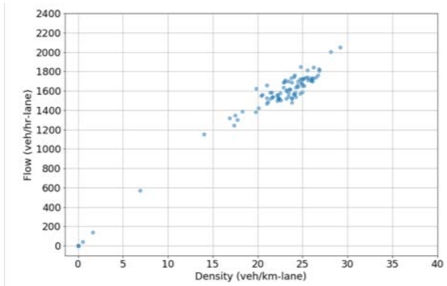
Figure 18 shows the fundamental diagrams of isolated-automated driving scenarios at each market penetration rate. Those diagrams show that automated driving can significantly improve traffic throughput and stability at medium-to-high (>60%) market penetration rates. The improvement in traffic performance is higher than with connectivity alone due to the highly responsive and robotic driving behavior of automated vehicles, which is fundamentally different from human drivers. Figure 19 shows the travel time distribution of the isolated-automated driving scenarios. As expected, automated driving improves the travel time of individual vehicles. The figures show that the distributions at low-medium market penetration rates shifts significantly towards lower values. In the 90 percent market penetration case, most vehicles drive at free flow speed.



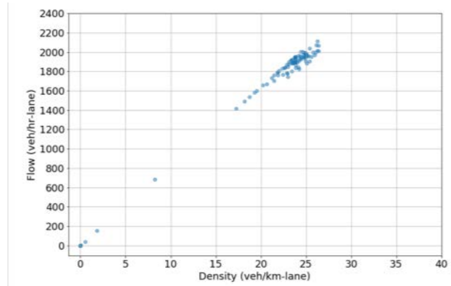
a) Base (100 percent regular vehicles).



b) Automated vehicle market penetration at 30 percent.

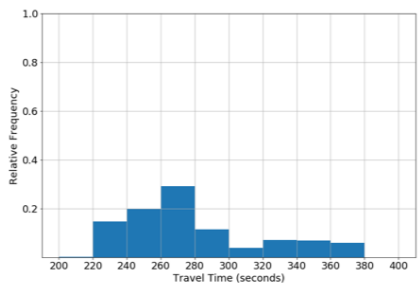


c) Automated vehicle market penetration at 60 percent.

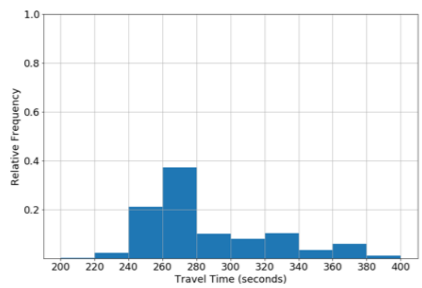


d) Automated vehicle market penetration at 90 percent.

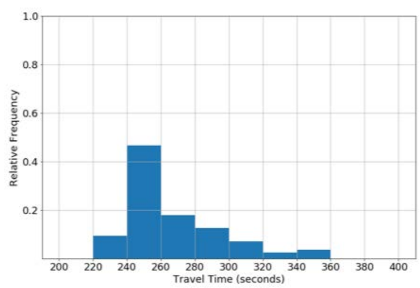
Figure 18. Fundamental diagrams for low, medium, and high isolated-automated vehicle market penetration rates.



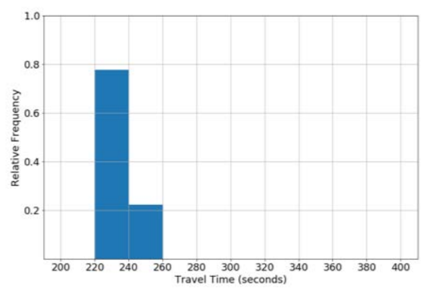
a) Base (100 percent regular vehicles).



b) Automated vehicle market penetration at 30 percent.



c) Automated vehicle market penetration at 60 percent.



d) Automated vehicle market penetration at 90 percent.

Figure 19. Travel time distributions for low (30 percent), medium (60 percent), and high (90 percent) isolated-automated vehicle market penetration rates.

Impact of Connected Automated Driving on Traffic Performance

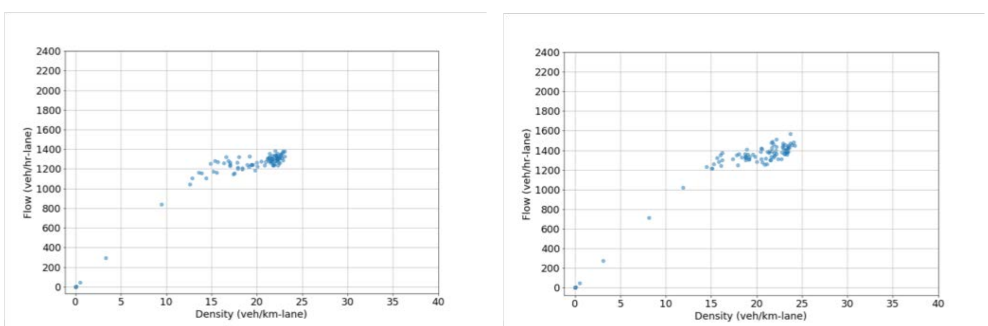
The following set of scenarios, summarized in Table 23, is intended to evaluate the impact of connected-automated driving behavior on traffic performance. Unlike isolated-automated vehicles, connected-automated vehicles rely on both their sensors and wireless telecommunication for perceiving the surrounding environment and control logic. The models used in these scenarios are different in two main ways: 1) the longitudinal car-following behavior assumes a significantly higher sensor range (300m) due to the fusion of information sources by those vehicles (*134*), and 2) lane-changing behavior assumes a connected environment, which is more responsive, as discussed in the modeling framework. (See the discussion of the Lane-changing Model in Chapter 9 for more information.)

Table 23. Connected-automated driving scenarios based on market penetration rate (percent).

Scenario Description	Isolated-Human (RV)	Connected-Human (CV)	Isolated-Automated (AV)	Connected-Automated (CAV)
Baseline – Human	**100**	0	0	**0**
Low CAV	**70**	0	0	**30**
Medium CAV	**40**	0	0	**60**
High CAV	**10**	0	0	**90**

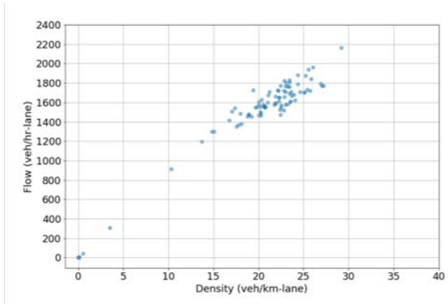
Source: FHWA 2018

Figure 20 shows the fundamental diagrams for the connected-automated driving scenarios. The graphs show that connected-automated driving can lead to significant improvements in traffic throughput and stability at medium to high market penetration rates, as in the case of isolated-automated driving. This improvement is slightly greater than that of isolated-automated scenarios. This is due to the higher sensor range assumed for those vehicles. Similarly, Figure 21 shows that connected-automated driving can lead to significant improvements in travel time, as seen in the distribution shift to lower travel time values. This improvement is also higher than that of the isolated-automated vehicle scenarios.

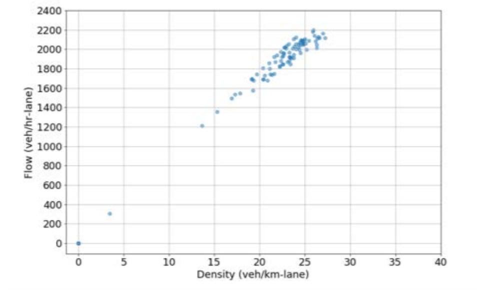


a) Base (100 percent regular vehicles).

b) Connected vehicle market penetration at 30 percent.

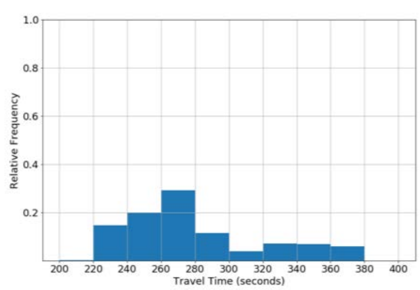


c) Connected vehicle market penetration at 60 percent.

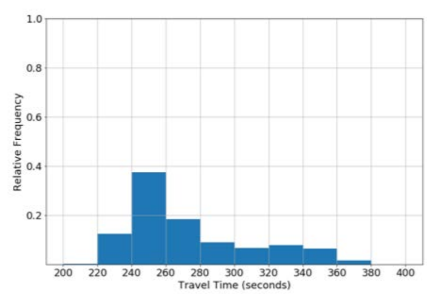


d) Connected vehicle market penetration at 90 percent.

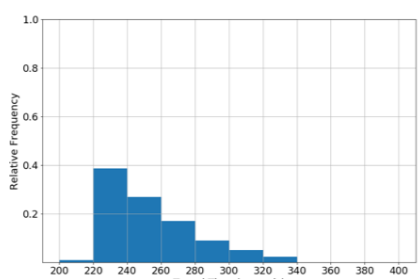
Figure 20. Fundamental diagrams for low, medium, and high connected-automated vehicle market penetration rates.



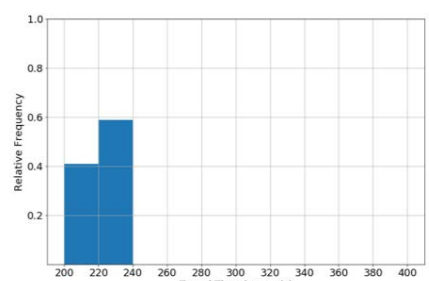
a) Base (100 percent regular vehicles).



b) Connected vehicle market penetration at 30 percent.



c) Connected vehicle market penetration at 60 percent.



d) Connected vehicle market penetration at 90 percent.

Figure 21. Travel time distributions for low, medium, and high connected-automated vehicle market penetration rates.

Impact of AV Sensor Performance on Mixed Traffic Flow

Sensor performance is a key element of CAV systems and directly affects their operational performance (*26*). This is more critical in the case of AVs as they rely almost exclusively on those sensors for environment perception and maneuvering (longitudinal and lateral). For example, an AV needs to estimate the distance to the front vehicle and its speed so that the AV can accelerate and decelerate safely. An AV also needs to detect surrounding vehicles to be able to change lanes safely and efficiently.

Despite the integral role sensor performance plays in CAV operations, a representation of it is missing in almost all existing CAV AMS capabilities. Those tools typically assume perfect operating conditions where sensors are fully reliable. This an unrealistic assumption since sensor performance degrades under certain conditions, such as in the case of severe weather conditions (low visibility, reflective road) or in the case of a sensor damage or malfunction.

The sub-optimal sensor operating scenarios can negatively impact the driving behavior of CAV systems and, therefore, needs to be captured in CAV AMS systems. For example, the lower detection range of AVs under severe weather conditions can affect the speed at which those vehicles operate and the size of the safe gap they require to change lanes. Furthermore, missing sensor representations in those performance models would reduce the capability CAV AMS systems to answer important questions related to the operation of CAV systems in the event of system failure as well as the impact of those failures on traffic flow; e.g., How would the driving behavior of an L2 AV vehicle transition to manual driving in the case of sensor failure, and how would that impact the traffic flow? Would that extra reaction time create a shockwave? This is also important for answering cyber-security related questions; e.g., How would the vehicle operate if the information it receives is tampered with, and how would that affect the performance of the whole system? This case study attempts to answer some of the traffic performance questions by modifying the AV car-following models.

Methodology

The scenarios in this section evaluate two types of sensor performance attributes that affect the performance of automated vehicles and, therefore, the overall performance of traffic flow. Those are the 1) distance measurement error (to a leading vehicle) and 2) vehicle sensor detection range. Distance measurement error directly impacts the car-following behavior of automated vehicles. If, for example, a measured distance is greater than it should be, an automated vehicle could accelerate more aggressively given the additional measured distance. As for AVs' sensor detection range, it directly affects the maximum speed at which vehicles can drive and, therefore, the overall speed of traffic stream.

Distance measurement in AV car-following models is assumed to have no errors, an assumption that is unrealistic in a real-world scenario. To address this limitation, an error term ε_D was added to the acceleration formula of automated vehicles as follows:

$$a_i^d(t) = k_a a_{i-1}(t-\tau) + k_v\big(v_{i-1}(t-\tau) - v_i(t-\tau)\big) + k_d((s_i + \varepsilon_D)(t-\tau) - s_{ref}) \quad [15]$$

Where a_i^d is the acceleration of vehicle i; k_a, k_v, and k_d are model parameters; s_i is vehicle spacing; and s_{ref} is the minimum between minimum distance (s_{min}), following distance based on the reaction time (s_{system}). This error term captures the stochasticity in sensor performance. Since actual data on sensor performance is limited, due to the confidentiality of automated vehicle development, a sensitivity analysis was performed for sensor range error between 10 percent and 30 percent. The error term is assumed to be uniformly distributed between a = -error rate and b = +error rate. For example, if an error term of 10 percent is evaluated and sensor range is 100m, then the error term distribution parameters would -10 and 10.

As for sensor detection range, current car following models assume perfect operational conditions with fully reliable sensors. In a real-world scenario, however, sensor range can be affected by factors such as low visibility or inclement weather conditions. To capture this variation in detection range, a negative error term ε_R was added to the maximum speed formula of automated vehicles as follows:

$$\Delta x = Sensor\ Detection\ Range + \varepsilon_R$$

$$v_{max} = \sqrt{-2a_i^{decc}\Delta x} \qquad [16]$$

where i and $i-1$ represent the automated vehicle and its leader, respectively; x_i is the location of vehicle i; l_i is the length of vehicle i; v_i is the speed of vehicle i; τ is the reaction time of vehicle i; and a_i^{decc} is the maximum deceleration of vehicle i. As in the case of the distance measurement error, a sensitivity analysis was conducted for range of sensor drops between 10 percent and 30 percent. The error term was also assumed to be uniformly distributed between 0 and error rate.

Results and Discussion

Distance Measurement Error Scenarios – Low AV Market Penetration (30 percent)

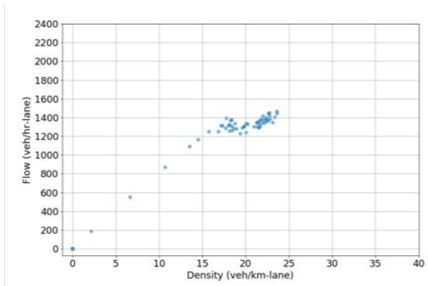
The following scenarios, summarized in Table 24, evaluate the impact of distance measurement error on traffic flow performance and travel time. Three main error rates were considered: 10 percent, 20 percent, and 30 percent. In those scenarios, a mixed traffic condition was assumed with a low AV market penetration rate. This low penetration rate tests how the distance measurement error would affect the overall traffic performance at early deployment of the technology.

Table 24. Distance measurement error scenarios in the low (30 percent) AV market penetration condition (percent).

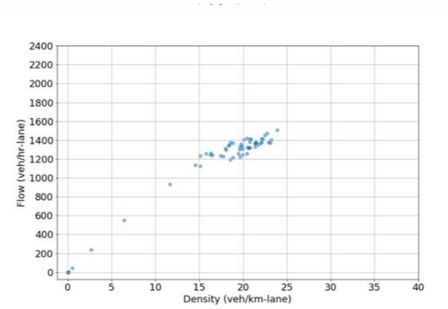
Scenario Description	Isolated-Human	Isolated-Automated	Measurement Error (ε_D) – Distance to Lead Vehicle
Low AV - Perfect Sensor Performance	70	30	0
Low AV – 10% error	70	30	10
Low AV – 20% error	70	30	20
Low AV – 30% error	70	30	30

Source: FHWA 2018

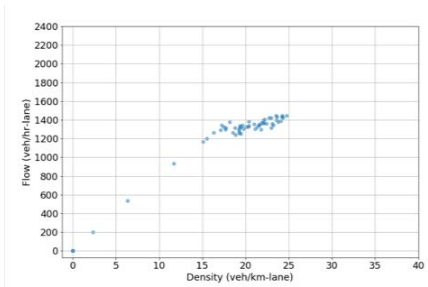
Figure **22** shows the fundamental diagrams for distance measurement error scenarios in low AV market penetration conditions (30 percent). As seen from the graphs, distance measurement error has minimal impact on traffic flow throughput and stability due to the low number of AVs in those scenarios. Similarly, as seen from the almost unchanged distributions in Figure 23, distance measurement errors cause no significant change to travel time.



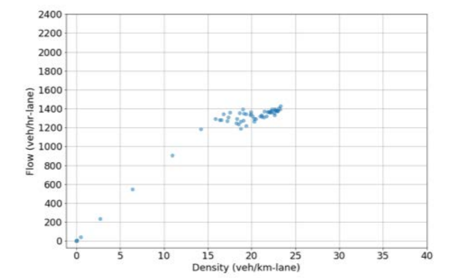
a) Perfect performance
(0 percent error).



b) 10 percent error.

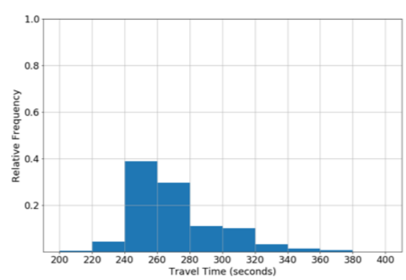


c) 20 percent error.

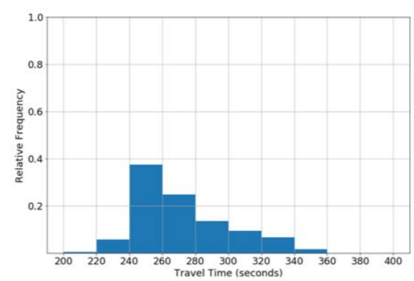


d) 30 percent error.

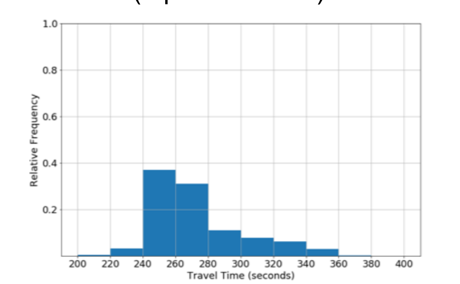
Figure 22. Fundamental diagrams for distance measurement error scenarios at a low (30 percent) AV market penetration rate.



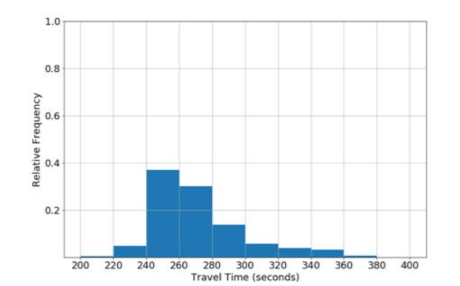
a) Perfect performance
(0 percent error).



b) 10 percent error.



c) 20 percent error.



d) 30 percent error.

Figure 23. Travel time distribution for distance measurement error scenarios at a low (30 percent) AV market penetration rate.

Distance Measurement Error Scenarios – High AV Market Penetration (70 percent)

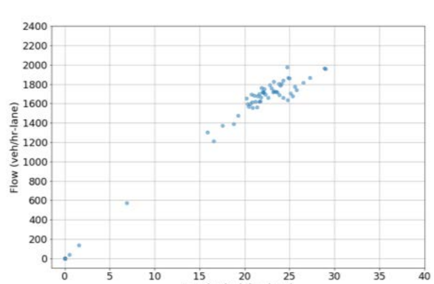
The scenarios shown in Table 25 evaluate the impact of distance measurement errors in highly automated traffic streams (70 percent). Error rates of 10 percent, 20 percent, and 30 percent were considered and compared to the baseline scenario of perfect (zero error) performance. Those scenarios test whether the distance measurement error has a higher impact on traffic performance than the previously tested scenarios of low traffic automation.

Table 25. Distance measurement error scenarios in the low (30 percent) AV market penetration condition (percent).

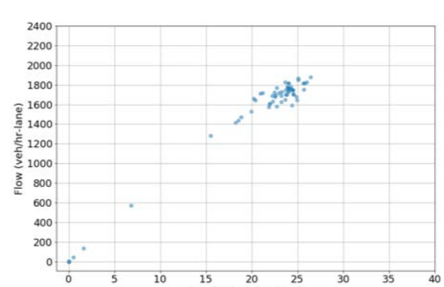
Scenario Description	Isolated-Human	Isolated-Automated	Measurement Error (ε_D) – Distance to Lead Vehicle
High AV - Perfect Sensor Performance	30	70	0
High AV – 10% error	30	70	10
High AV – 20% error	30	70	20
High AV – 30% error	30	70	30

Source: FHWA 2018

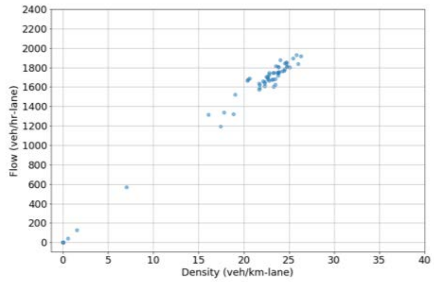
Figure 24 shows the fundamental diagrams for the distance measurement error scenarios in high AV market penetration conditions (70 percent). The figures show that an error rate of 30 percent could lead to a marginal increase in traffic flow. While this result may seem counterintuitive at first glance, this may indicate that the errors can lead to more aggressive driving behavior (higher acceleration) due to the higher perception of safety by automated vehicles that measure a distance that is higher than the actual one—for the particular logic modeled in this exercise. However, this result is only seen at the higher error rate scenario (30 percent), where measurement error is significant enough to affect driving behavior. It is also evident in highly automated traffic streams where there are enough AV vehicles to impact the overall performance of the traffic stream. Figure 25 shows the travel time distributions for the same scenarios. As seen in the graphs, the higher error rate of 30 percent could lead to a small shift in the distribution toward lower travel time values, which confirms the potentially aggressive driving of some AVs under the current logic modeled in this illustration.



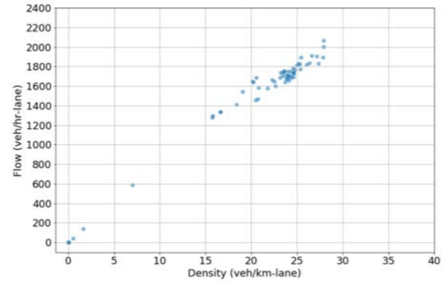
a) Perfect performance (0 percent error).



b) 10 percent error.

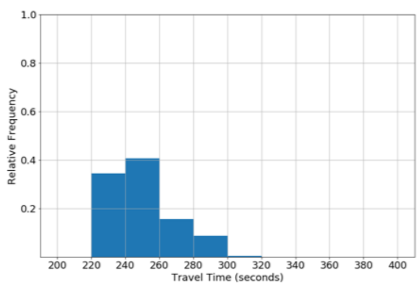


c) 20 percent error.

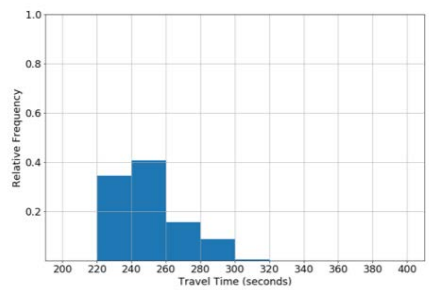


d) 30 percent error.

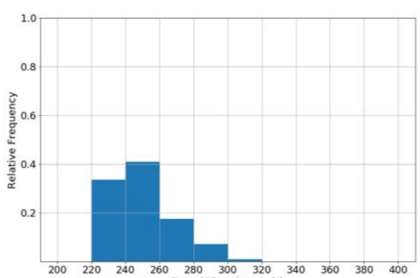
Figure 24. Fundamental diagrams for distance measurement error scenarios at a high (70 percent) AV market penetration rate.



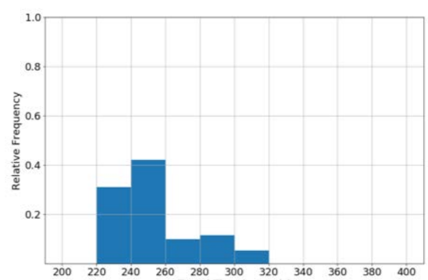
a) Perfect performance
(0 percent error).



b) 10 percent error.



c) 20 percent error.



d) 30 percent error.

Figure 25. Travel time distribution for distance measurement error scenarios at a high (70 percent) AV market penetration rate.

Distance Measurement Error Scenarios – High CAV Market Penetration (70 percent)

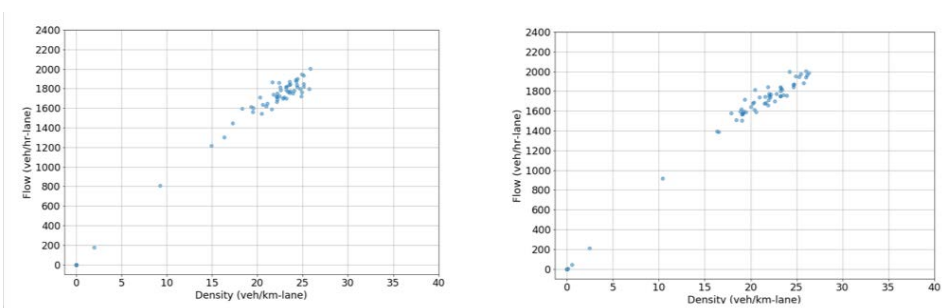
Table 26 shows the simulated scenarios to evaluate the impact distance measurement errors for highly connected and automated traffic streams (CAV 70 percent). Similar to previous scenarios, three error rates ranging from 10 percent to 30 percent were tested.

Table 26. Distance measurement error scenarios in the high (70 percent) CAV market penetration condition.

Scenario Description	Isolated-Human	Connected-Automated	Measurement Error (ε_D) – Distance to Lead Vehicle
High CAV - Perfect Sensor Performance	30	70	0
High CAV – 10% error	30	70	10
High CAV – 20% error	30	70	20
High CAV – 30% error	30	70	30

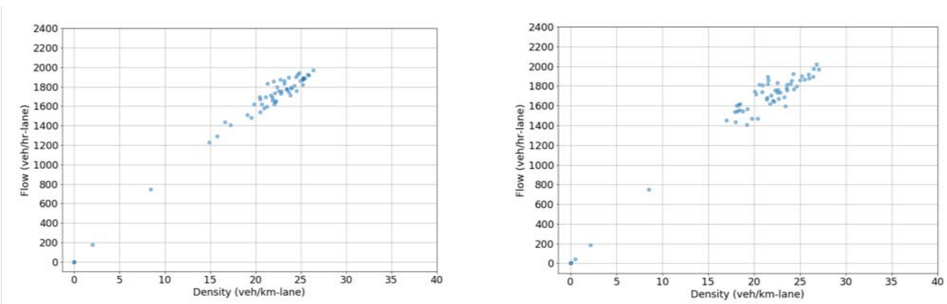
Source: FHWA 2018

Figure 26 shows the fundamental diagrams for the distance measurement error scenarios in high CAV market penetration conditions (70 percent). As in the case of the highly automated stream scenarios tested in a previous section, the graphs show that high error rates (30 percent) can lead to a small increase in traffic throughput due to the potential for more aggressive driving among some vehicles. While connectivity in this modeling framework improves the range of sensors due to the fusion of different data sources (sensors and other vehicles through wireless telecommunication), it does not improve the sensors' measurement accuracy. Therefore, the overall impact of errors is similar to the case of isolated-automated traffic streams. Figure 27 shows the travel time distributions of the aforementioned scenarios. The graphs indicate that the errors in those scenarios have minimal impact on travel time distribution among individual vehicles. This shows that the change in driving behavior is not significant enough to impact travel time. Note that in the case of low CAV market penetration, the impact of distance measurement errors on both traffic performance and travel time was insignificant.



a) Perfect performance (0 percent error).

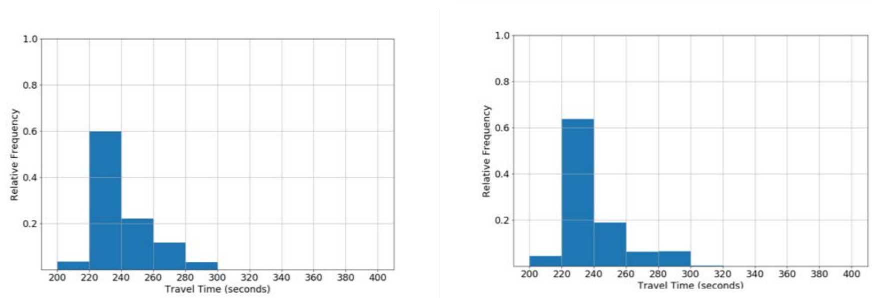
b) 10 percent error.



c) 20 percent error.

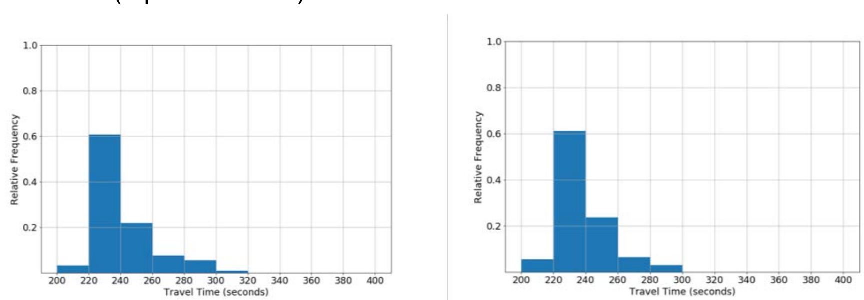
d) 30 percent error.

Figure 26. Fundamental diagrams for distance measurement error scenarios at a high (70 percent) CAV market penetration rate.



a) Perfect performance
(0 percent error).

b) 10 percent error.



c) 20 percent error.

d) 30 percent error.

Figure 27. Travel time distribution for distance measurement error scenarios at a high (70 percent) CAV market penetration rate.

Sensor Range Reduction Scenarios – Low AV Market Penetration (30 percent)

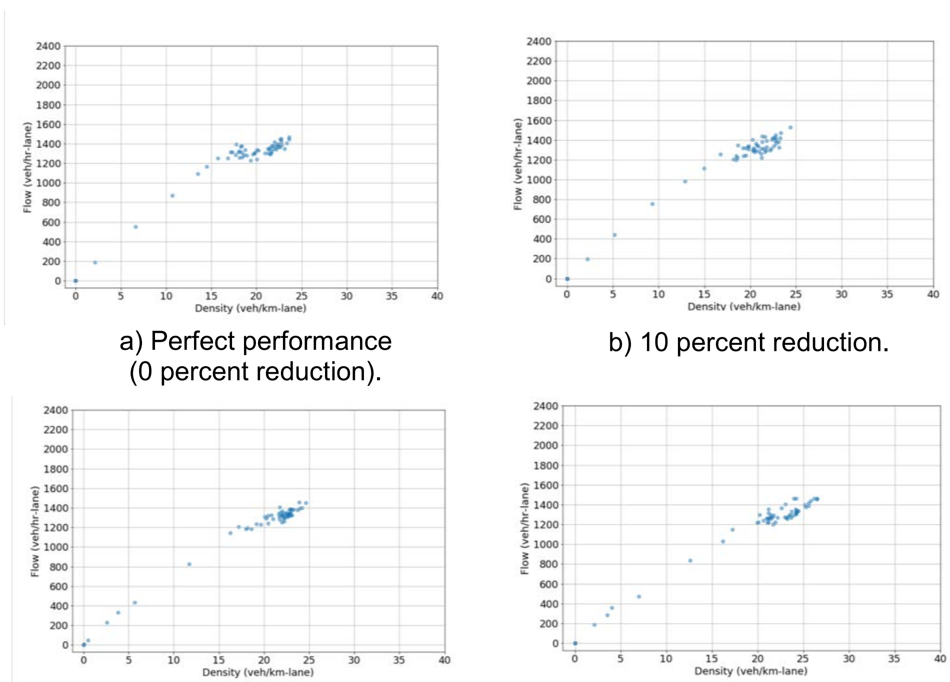
As mentioned in the methodology section, sensor range drops can affect the maximum speed at which automated vehicles travel. The scenario set summarized in Table 27 evaluates the impact of sensor range reductions on overall traffic performance in the case of low automation (30 percent AV). Three range reductions were tested: 10 percent, 20 percent, and 30 percent.

Table 27. Sensor range reduction scenarios in the low (30 percent) AV market penetration condition (percent).

Scenario Description	Isolated-Human	Isolated-Automated	Sensor Range Drop (ε_R)
Low AV - Perfect Sensor Performance	70	30	0
Low AV – 10% reduction	70	30	10
Low AV – 20% reduction	70	30	20
Low AV – 30% reduction	70	30	30

Source: FHWA 2018

Figure 28 shows the fundamental diagrams for the range reduction scenarios in low AV market penetration conditions (30 percent). The graphs show that range detection has insignificant impact on traffic throughput. This is because human-driven vehicles are dominating and are not affected by range drop. However, the graphs also indicate higher traffic stability (less scatter) above the 20 percent reduction range. This is due to the lower overall speed of the traffic and less aggressive driving. Figure 29 shows the travel time distributions for the same scenarios. Those graphs indicate that range reductions greater than 20 percent can lead to longer travel time due to lower speeds among AVs, as seen from the distribution shift to higher values (right).



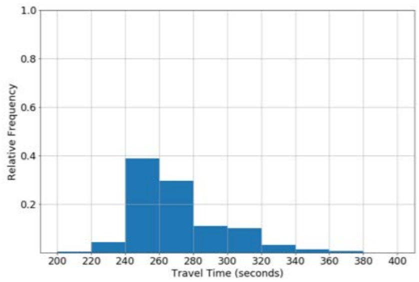
a) Perfect performance (0 percent reduction).

b) 10 percent reduction.

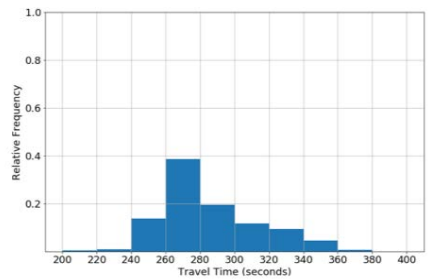
c) 20 percent reduction.

d) 30 percent reduction.

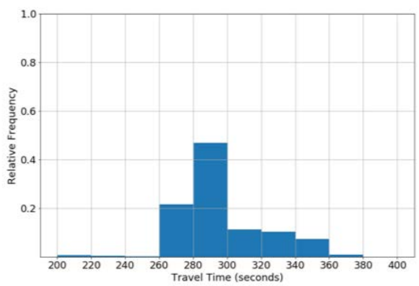
Figure 28. Fundamental diagrams for sensor range reduction scenarios at a low (30 percent) AV market penetration rate.



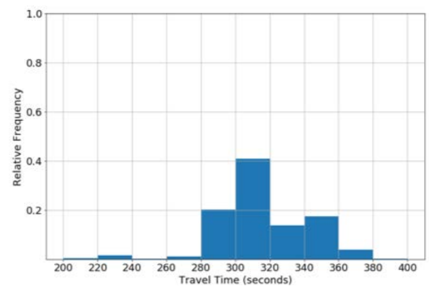
a) Perfect performance
(0 percent reduction).



b) 10 percent reduction.



c) 20 percent reduction.



d) 30 percent reduction.

Figure 29. Travel time distribution for sensor range reduction scenarios at a low (30 percent) AV market penetration rate.

Sensor Range Reduction Scenarios – High AV Market Penetration (70 percent)

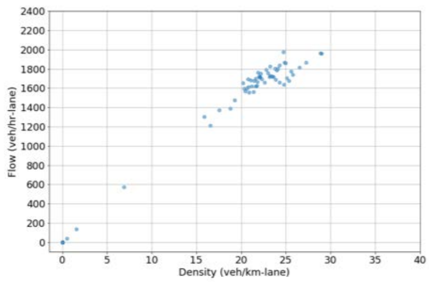
The scenarios summarized in Table 28 evaluate the impact of sensor range reductions in highly automated traffic streams. Three reduction rates were tested: 10 percent, 20 percent, and 30 percent.

Table 28. Sensor range reduction scenarios in the high (70 percent) AV market penetration condition (percent).

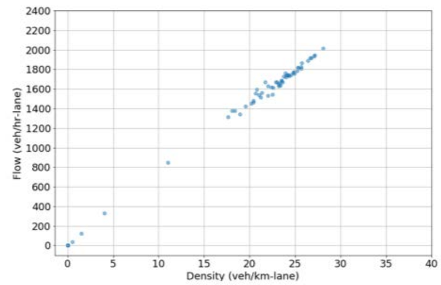
Scenario Description	Isolated-Human	Isolated-Automated	Sensor Range Drop (ε_R)
High AV - Perfect Sensor Performance	30	70	0
High AV – 10% reduction	30	70	10
High AV – 20% reduction	30	70	20
High AV – 30% reduction	30	70	30

Source: FHWA 2018

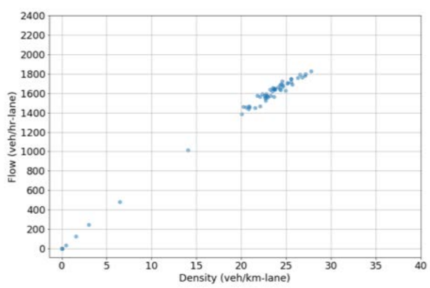
Figure 30 shows the fundamental diagrams for the sensor range reduction scenarios in high AV market penetration conditions (70 percent). Those graphs show that range drops greater than 20 percent lead to reductions in traffic flow throughput due to lower speeds of automated vehicles. The reduction in throughput is more significant than traffic with low AV penetration as the high number of vehicles is significant enough to change the overall performance of traffic. The overall reduction in speed, however, can lead to better stability (less scatter) due to less aggressive driving. Figure 31 shows the travel time distribution of the same scenarios. The graph shows that sensor range drops can lead to higher travel time as seen in the distribution shift towards higher values (right) which confirms the lower overall vehicle speed as a result of the sensor range drop.



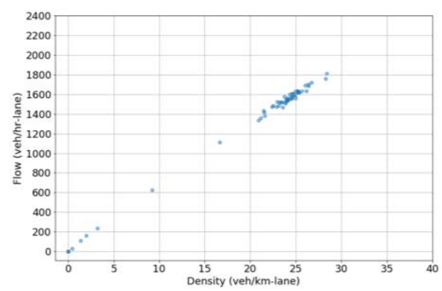
a) Perfect performance (0 percent reduction).



b) 10 percent reduction.

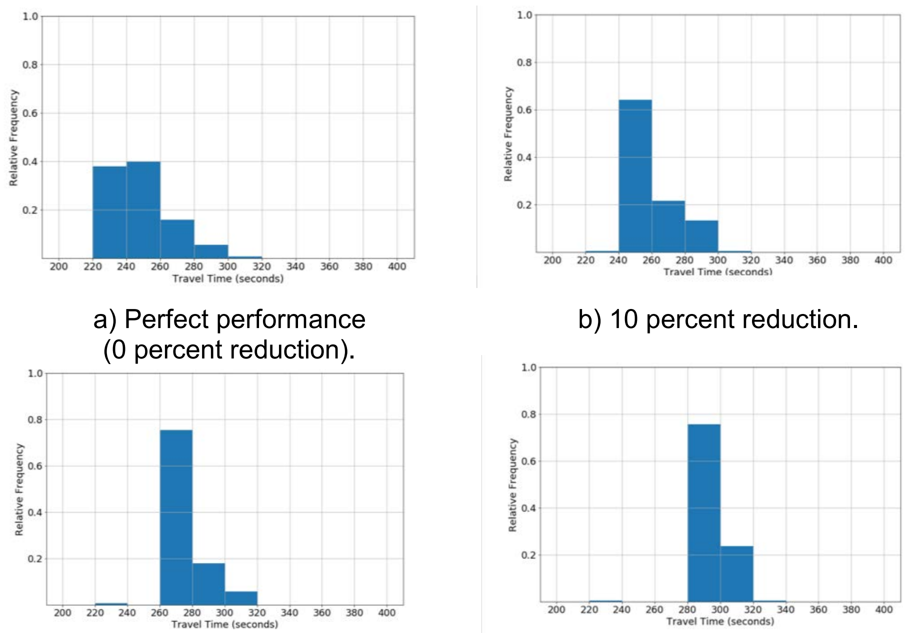


c) 20 percent reduction.



d) 30 percent reduction.

Figure 30. Fundamental diagrams for sensor range reduction scenarios at a high (70 percent) AV market penetration rate.



a) Perfect performance (0 percent reduction).

b) 10 percent reduction.

c) 20 percent reduction.

d) 30 percent reduction.

Figure 31. Travel time distribution for sensor range reduction scenarios at a high (70 percent) AV market penetration rate.

Sensor Range Reduction Scenarios – High AV Market Penetration (70 percent)

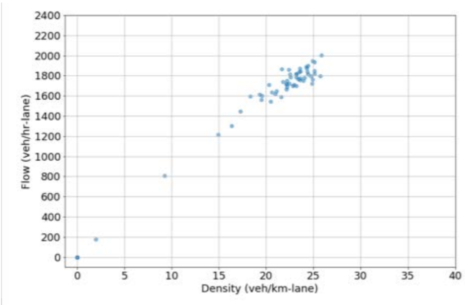
The scenario set summarized in Table 29 evaluates the impact of sensor range reduction for highly connected and automated traffic streams (70 percent CAV). As mentioned in the methodology section, CAVs have a higher range than AVs due to the additional information received by CAVs through wireless telecommunication. The scenarios tests three reduction rates: 10 percent, 20 percent, and 30 percent.

Table 29 Sensor range reduction scenarios in the high (70 percent) AV market penetration condition (percent).

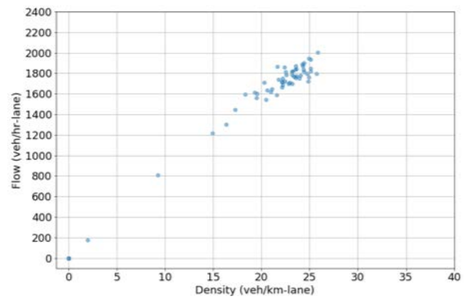
Scenario Description	Isolated-Human	Connected-Automated	Sensor Range Drop (ε_R)
High CAV - Perfect Sensor Performance	30	70	0
High CAV – 10% reduction	30	70	10
High CAV – 20% reduction	30	70	20
High CAV – 30% reduction	30	70	30

Source: FHWA 2018

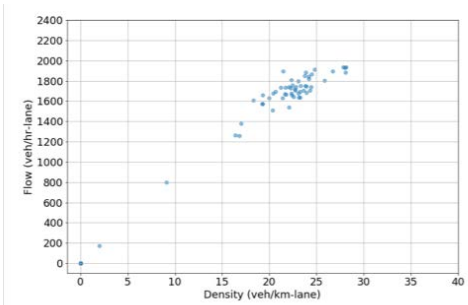
Figure 32 shows the fundamental diagrams for the sensor range reduction scenarios in high CAV market penetration conditions (70 percent). The plots show that range reduction for CAVs has insignificant impact on the traffic throughput and stability. Since CAVs have a higher detection range than AV, the reduced range is still higher than the minimum range required to achieve speed limits. Therefore, the speed of vehicles has not changed. This is also confirmed by Figure 33 which shows that travel time distributions have not changed as a result of the range drop, indicating that vehicle speed has not changed. As for the low CAV scenarios (30 percent), range has insignificant impact on traffic throughput and travel time due to the low number of CAVs (dominating human driving behavior).



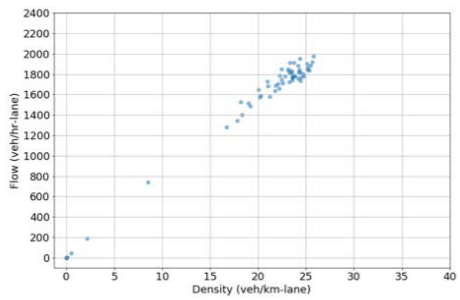
a) Perfect performance
(0 percent reduction).



b) 10 percent reduction.

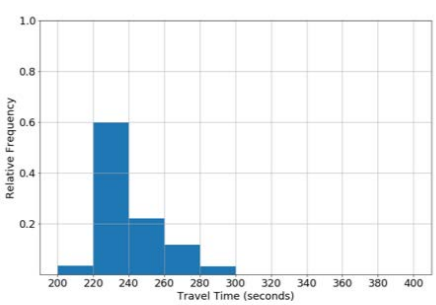


c) 20 percent reduction.

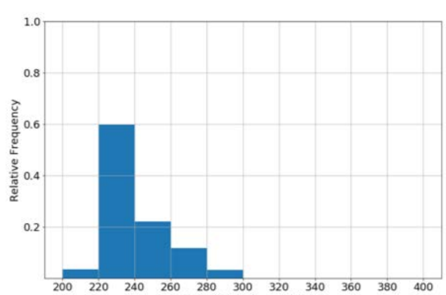


d) 30 percent reduction.

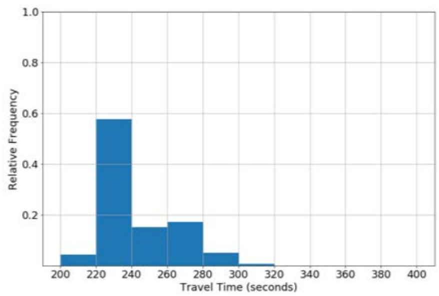
Figure 32. Fundamental diagrams for sensor range reduction scenarios at a high (70 percent) AV market penetration rate.



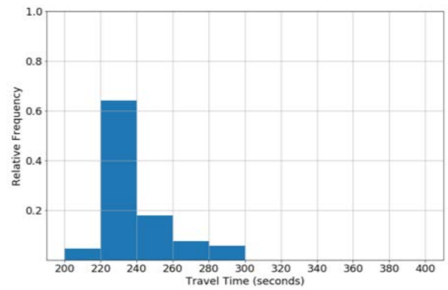
a) Perfect performance
(0 percent reduction).



b) 10 percent reduction.



c) 20 percent reduction.



d) 30 percent reduction.

Figure 33. Travel time distribution for sensor range reduction scenarios at a high (70 percent) CAV market penetration rate.

Impact of Automated Truck Platooning in Mixed Traffic Flow

Truck platooning links multiple trucks in a convoy using wireless telecommunications and automated control systems. The algorithm assigns one truck to be designated as the leader and others in the convoy adjust their speeds to that of the leading vehicle, following each other at short distances. Truck platooning can rely on CACC technology to control longitudinal movement by adjusting the speeds of following trucks or, as envisioned for future systems, use fully automated driving functions (longitudinal and lateral) that rely on wireless telecommunications and vehicle sensors.

Truck platooning has potential safety, mobility, and sustainability benefits. In terms of safety, platooning can improve the reaction of connected trucks over individual trucks as the platooned vehicles can adjust their speeds to that of the leading vehicle, minimizing the likelihood of an accident due to a slower reaction. This can improve further if the leading truck is automated and uses multiple sensors to detect traffic around it. As for mobility benefits, truck platooning can improve the efficiency of operating trucks on the road, which can improve the traffic state. Finally, moving at short distances reduces air drag between trucks significantly and therefore improves fuel consumption, lowers emissions, and reduces overall costs.

As the percentage of trucks on some interstates can be significant, trucks can be a significant factor in the performance of mixed traffic as a whole. This case study focuses on modeling truck platooning in a mixed connected environment to evaluate the overall operational performance. To do this, a modeling framework of automated truck platooning developed by PATH at the University of California, Berkeley (*135*) was adopted and integrated into the testbed's microsimulation platform. The modeling framework is discussed in the methodology section below.

Methodology

The truck platooning modeling framework adopted in this study was developed by PATH at the University of California, Berkeley (*135; 136*). This framework has three distinct driving behaviors for automated trucks: 1) cruise control, 2) adaptive cruise control, and 3) cooperative adaptive cruise control. Below is a description of each of those behaviors. The model parameters were calibrated using experimental data collected by researchers at PATH (*135; 136*).

Cruise Control (CC)

The cruise control car-following behavior captures automated truck driving in free flow conditions (no leading vehicle) or when a time gap to a leading vehicle is above a certain threshold (2.5 seconds). Through this control logic, an automated truck maintains a desired speed—in this case, the freeway speed limit. The car following formula is as follows:

$$a_{Aut}(t) = k_p\ [v_{ref}(t-1) - v(t-1)] \qquad [17]$$

Where k_p is a model parameter (0.3907)

Adaptive Cruise Control (ACC)

The adaptive cruise control logic is activated when an automated truck is following another vehicle outside of a truck platoon. Following this logic, an automated truck aims to maintain a desired time gap (2 seconds) between itself and the leading vehicle. This logic applies to isolated-automated trucks or connected trucks driving outside a platoon. The car following model is as follows:

$$a_{Aut}(t) = k_1\ [d(t-1) - t_{des}^{ACC} v(t-1)] + \ k_2[v_{prec}(t-1) - v(t-1)] \qquad [18]$$

Where t_{des}^{ACC} is the desired time gap in ACC mode (2 sec), $v_{prec}(t-1)$ is speed of the preceding vehicle at time $(t-1)$, $k_1$and $k_2$are model parameters (0.0561 and 0.3393 respectively).

Cooperative Adaptive Cruise Control (CACC)

Cooperative adaptive cruise control is activated when a connected-automated truck is following another connected-automated truck in a platoon. With this control, the truck maintains a desired time gap in a platoon (1.5 seconds), which is shorter than the desired time gap of adaptive cruise control. Note that if a connected truck is outside a platoon (following a non-connected truck), the connected truck would then follow the ACC logic described above. The CACC car following formula is as follows:

$$a_{Aut}(t) = k_p e(t-1) + k_d \dot{e}(t-1) \qquad [19]$$

Where $e(t-1)$ is a measure of deviation from the CACC desired time gap, t_{des}^{CACC} is the desired time gap for CACC (1.5 seconds), $\dot{e}(t-1)$ is derivative of $e(t-1)$, and $k_p$and k_d are model parameters (0.0074 and 0.0805 respectively).

Truck Platoon Formation

An opportunistic platoon formation strategy is considered in this case study. An opportunistic formation refers to connected trucks forming platoons whenever possible without inducing any intervention such as pushing certain trucks to change a lane to form a platoon or using reserved lanes. Through this strategy, truck platooning behavior is activated whenever a connected truck is following another connected truck.

Impact of Automated Truck Platooning in Mixed Traffic Scenarios – Low Automation (30 percent AV) Condition

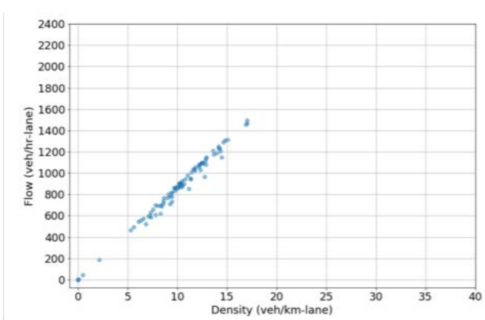
The scenarios summarized in Table 30 evaluate the impact of automated truck platooning at low AV market penetration (30 percent). The scenarios test platooning for two truck percentages of total traffic: 10 percent and 20 percent. The rest is a mix of AVs and human-driven cars.

Table 30. Automated truck platooning in mixed traffic scenarios – low (30 percent) AV market penetration condition (percent).

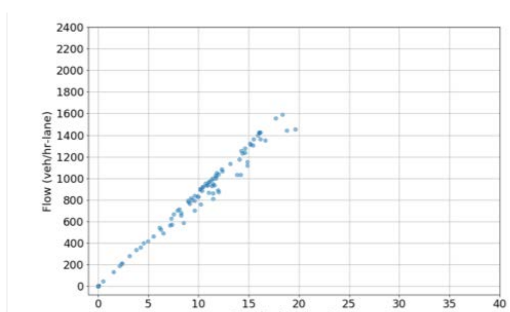
Scenario Description	Isolated-Manual Car	Isolated-Automated Car	Isolated-Automated Truck	Connected-Automated Truck
10% Trucks – No Platooning	60	30	10	0
10% Trucks – Active Platooning	60	30	0	10
20% Trucks – No Platooning	50	30	20	0
20% Trucks – Active Platooning	50	30	0	20

Source: FHWA 2018

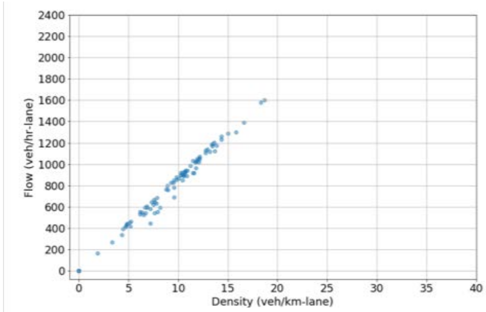
Figure 34 shows the fundamental diagrams of truck platooning scenarios in low AV market penetration conditions (30 percent). The diagrams show that in both the 10 percent and 20 percent truck percent cases, truck platooning can lead to improvements in traffic throughput (the right two diagrams). This can be caused by the homogenous and less aggressive driving behavior of trucks in platoons. This can also be due to higher traffic density as connected trucks follow each other at shorter distances. The impact of truck platooning on overall travel time, however, is insignificant, as seen in Figure 35. Overall travel time refers to the travel time distribution of all vehicles in traffic stream (trucks and cars). This is likely due to the small number of trucks in traffic stream and the opportunistic platoon formation strategy as discussed in the Methodology section above (a truck activates platooning whenever it follows another connected truck). Looking at the travel time distribution of trucks only, Figure 36, results show that truck platooning can lead to slightly higher travel times for trucks. This can be a result of the less aggressive driving within the truck platoons. On the other hand, truck platooning has no significant impact on the travel time distribution for cars (the majority of traffic stream) as shown in Figure 37. The lack of change in the overall travel time distribution indicates insignificant changes in traffic speed, which confirms that the small improvement in throughput is due to greater traffic density (trucks following each other at smaller distances).



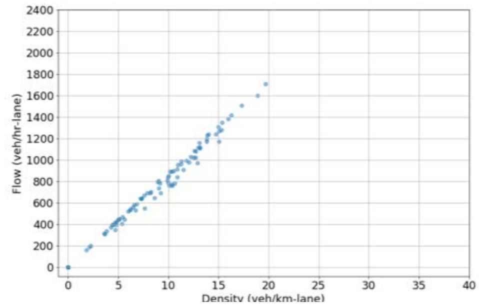
a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.



c) 20 percent trucks – no platooning.



d) 20 percent trucks – active platooning.

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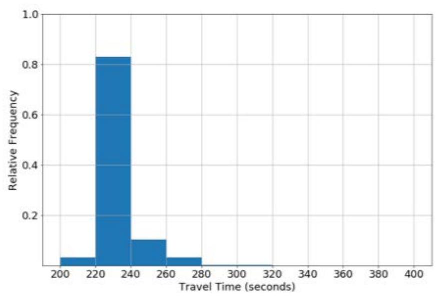
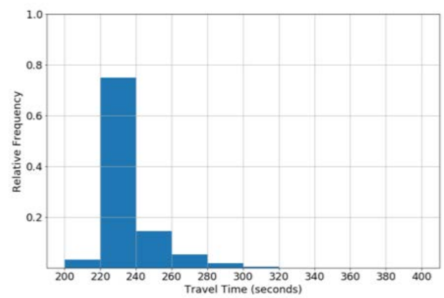
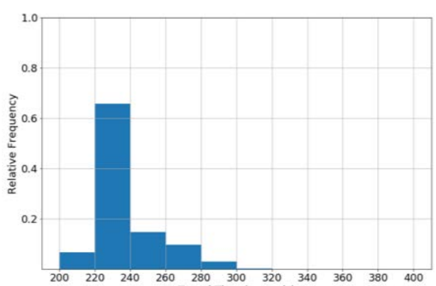
Figure 34. Fundamental diagrams for truck platooning scenarios at at a low (30 percent) AV market penetration rate.



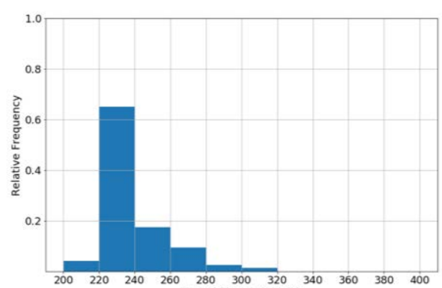
a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.



c) 20 percent trucks – no platooning.



d) 20 percent trucks – active platooning.

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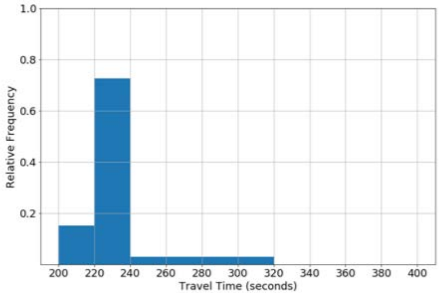
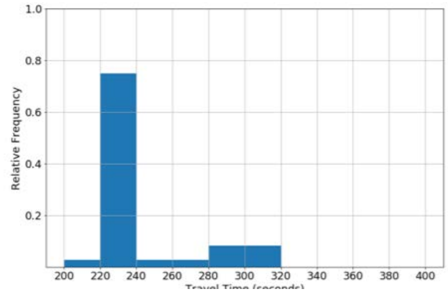
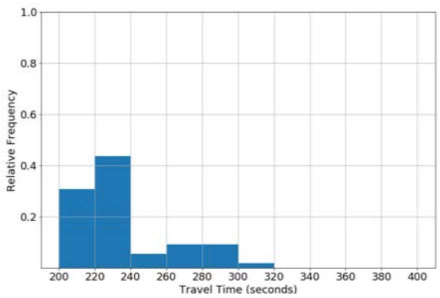
Figure 35. Overall travel time distribution for truck platooning scenarios at a low (30 percent) AV market penetration rate.



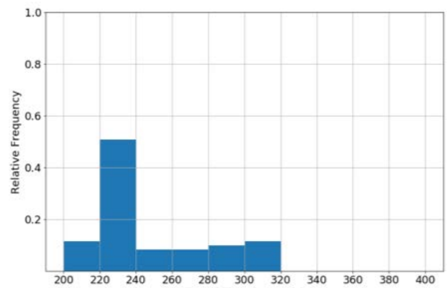
a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.

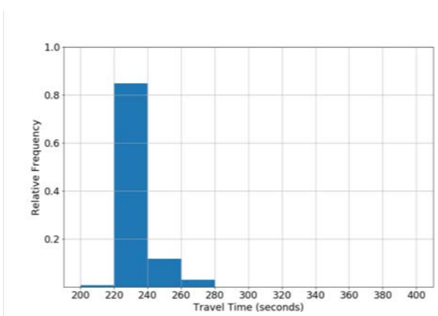


c) 20 percent trucks – no platooning.

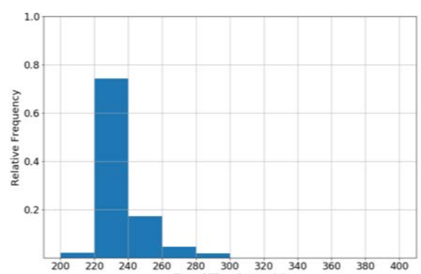


d) 20 percent trucks – active platooning.

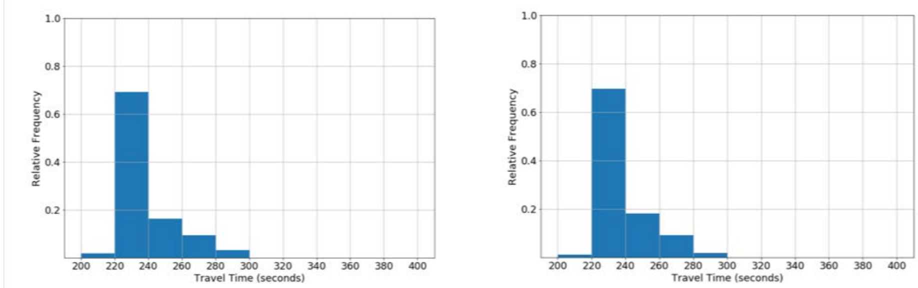
Figure 36. Truck travel time distribution for truck platooning scenarios at a low (30 percent) AV market penetration rate.



a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.



c) 20 percent trucks – no platooning.

d) 20 percent trucks – active platooning.

Figure 37. Car travel time distribution for truck platooning scenarios at a low (30 percent) AV market penetration rate.

Impact of Automated Truck Platooning in Mixed Traffic Scenarios – High Traffic Automation (70 percent AV)

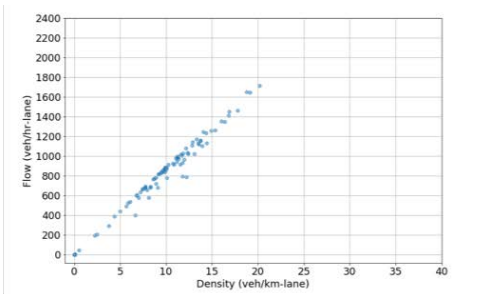
The scenarios summarized in Table 31 evaluate the impact of automated truck platooning at high AV market penetration (70 percent). The scenarios test platooning for two truck percentages of total traffic: 10 percent and 20 percent. The rest is a mix of AVs and human-driven cars.

Table 31. Automated truck platooning in mixed traffic scenarios – high (70 percent) AV market penetration condition (percent).

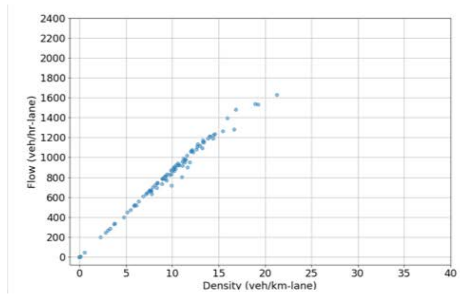
Scenario Description	Isolated-Manual Car	Isolated-Automated Car	Isolated-Automated Truck	Connected-Automated Truck
10% Trucks – No Platooning	20	70	10	0
10% Trucks – Active Platooning	20	70	0	10
20% Trucks – No Platooning	10	70	20	0
20% Trucks – Active Platooning	10	70	0	20

Source: FHWA 2018

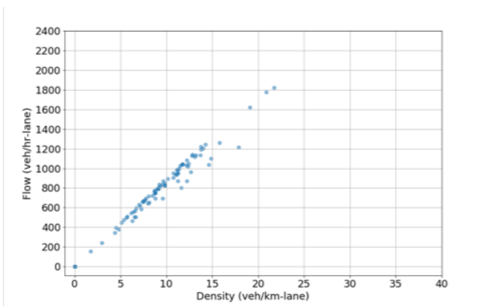
Figure 38 shows the fundamental diagrams for truck platooning scenarios in the high AV market penetration condition (70 percent). Similar to the low automation case, the diagrams show that activating truck platooning can lead to higher traffic throughput. This is because platooned vehicles do not drive aggressively and because they maintain a shorter time gap. Figure 39 shows the travel time distributions for the same scenarios. The plots indicate that truck platooning has an insignificant impact on the overall travel time of individual vehicles (no significant shifts in distributions). The small number of trucks in the traffic stream (< 20 percent) is likely the reason for this insignificant change in overall travel time. Looking more deeply into the trucks-only travel time distributions in Figure 40, the plots show that platooning can actually lead to greater travel time for trucks. This is likely due to the less aggressive driving behavior of platooned vehicles, which also maintaining shorter time gaps between each other compared to non-automated trucks. Figure 41 illustrates the cars-only travel time distribution. The plots show that platooning has insignificant impact on travel time for cars. This indicates that the changes in truck driving behavior is not significant enough to impact the car driving behavior and their travel time as the number of trucks is small in the traffic stream (< 20 percent). The insignificant change in travel time (and speed) also indicates that the small increase in traffic throughput is due to higher density (trucks within platoons driving at shorter distances) and not speed itself. While the general trends in the case of high traffic automation is similar to the low traffic automation case discussed previously, the overall throughput is higher and travel time is lower in the case of high automation due to the larger market penetration of AVs.



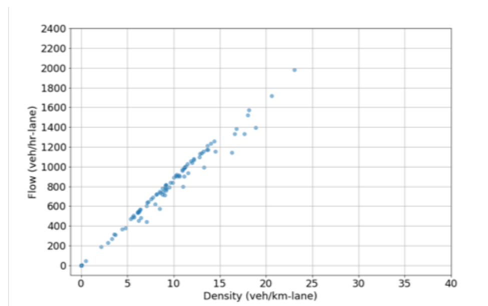
a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.

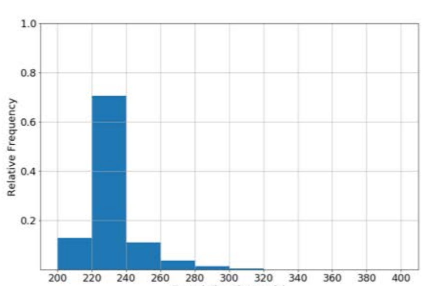


c) 20 percent trucks – no platooning.

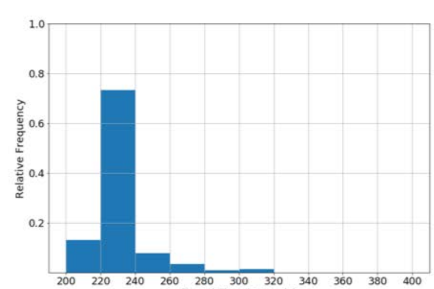


d) 20 percent trucks – active platooning.

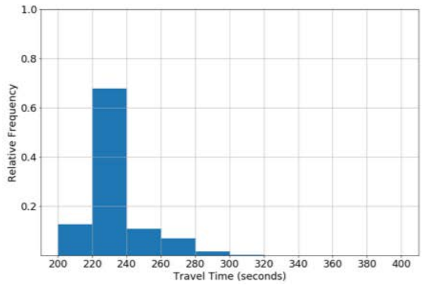
Figure 38. Fundamental diagrams for truck platooning scenarios at a high (70 percent) AV market penetration.



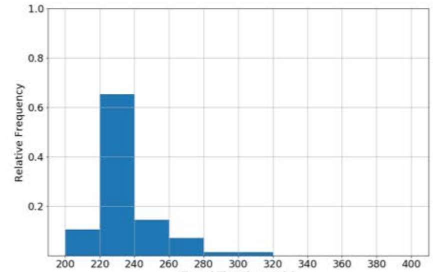
a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.

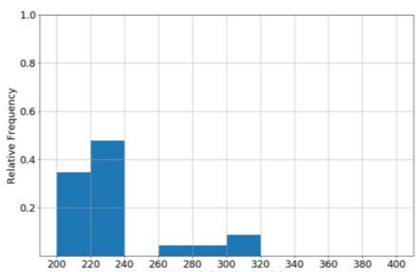


c) 20 percent trucks – no platooning.

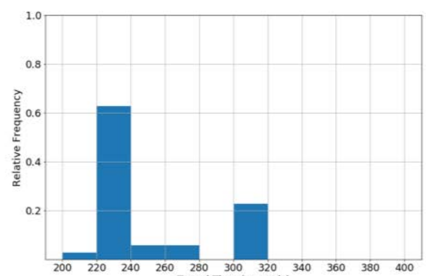


d) 20 percent trucks – active platooning.

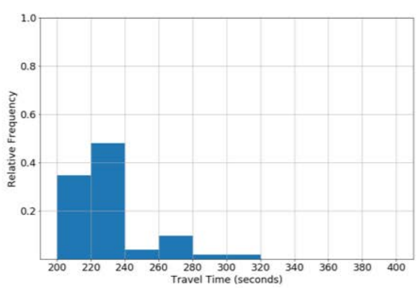
Figure 39. Overall travel time distribution for truck platooning scenarios at a high (70 percent) AV market penetration rate.



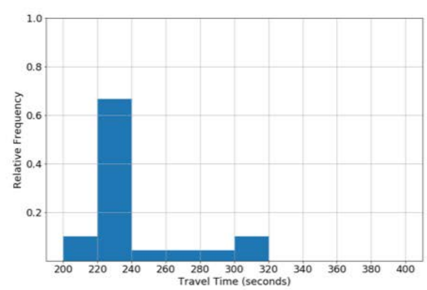
a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.

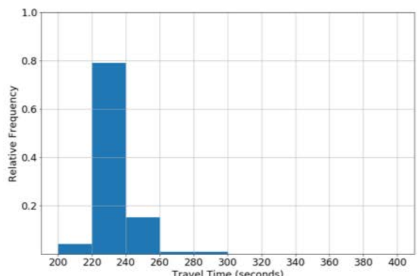


c) 20 percent trucks – no platooning.

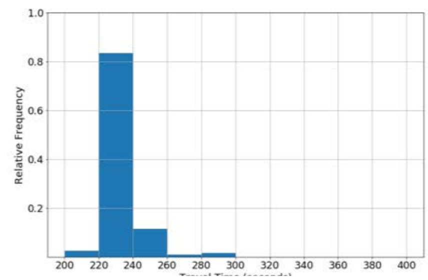


d) 20 percent trucks – active platooning.

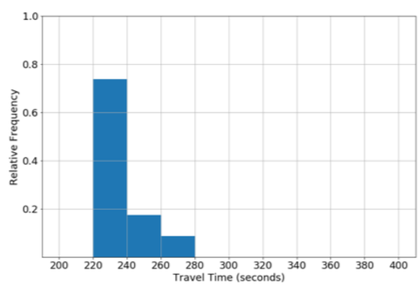
Figure 40. Truck travel time distribution for truck platooning scenarios at a high (70 percent) AV market penetration rate.



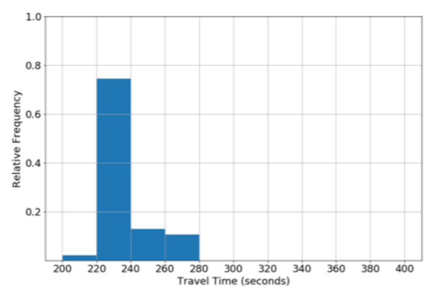
a) 10 percent trucks – no platooning.



b) 10 percent trucks – active platooning.



c) 20 percent trucks – no platooning.

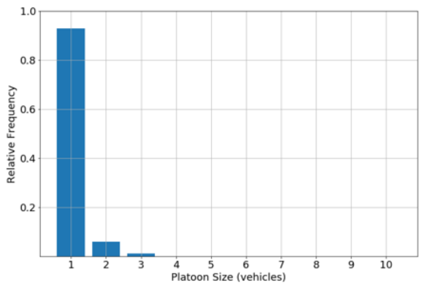


d) 20 percent trucks – active platooning.

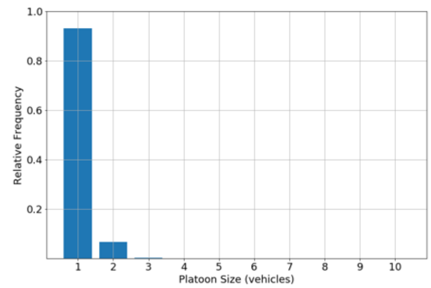
Figure 41. Car travel time distribution for truck platooning scenarios at a high (70 percent) AV market penetration rate.

Truck Platoon Size Analysis

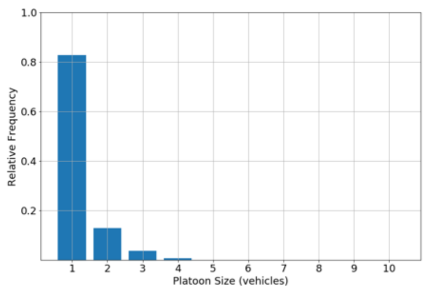
Figure 42 shows the platoon size distribution when trucks make up 10 percent and 20 percent of traffic under both the low and high market penetration rates for automated vehicles. The plots show that, when 10 percent of traffic is made up of trucks, the platoon size is 2-3 vehicles, while the majority of connected trucks (90 percent) are not in active platoons. Part of the reason for the small sizes is due to the opportunistic nature of platoon formation in this case study where connected trucks activate platooning behavior only if they follow other connected trucks (i.e., platoons are not predefined). The other part of the reason is due to the small number of trucks in the traffic stream, which makes it unlikely that a connected truck would be following another connected truck. The lower two plots of Figure 42 show platoon size when 20 percent of traffic is made up of trucks. In those cases, trucks form platoons more often than in the 10 percent composition scenario, and the range is 2-4 vehicles. This is due to the larger number of trucks in the traffic stream and, therefore, the higher likelihood of platoon formation.



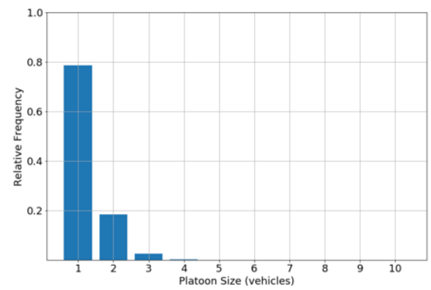
a) 10 percent trucks – low automation (30 percent AV).



b) 10 percent trucks – high automation (70 percent AV).



c) 20 percent trucks – low automation (30 percent AV).

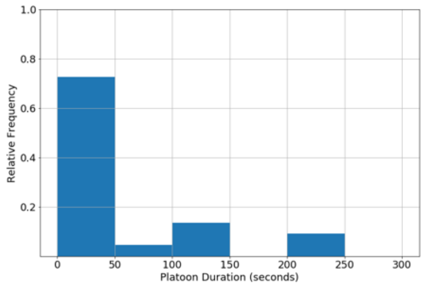


d) 20 percent trucks – high automation (70 percent AV).

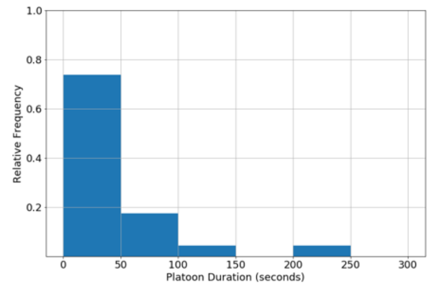
Figure 42. Truck platoon size for 10 percent/20 percent trucks at low (30 percent) and high (70 percent) AV market penetration levels.

Truck Platoon Duration Analysis

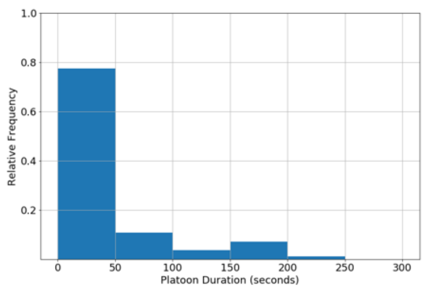
Figure 43 shows the platoon duration distribution when trucks make up 10 percent and 20 percent of traffic under both the low and high market penetration rates for automated vehicles. Duration in this context refers the numbers of seconds for which a platoon is moving in the traffic stream before it breaks (i.e., a truck leaves a platoon). The plots show that, generally, most platoons break after 50 seconds (220 second is the duration required to cross the study segment at free flow speed). This is due to the small number of trucks in the traffic stream (< 20 percent), the opportunistic nature of platoon formation, and the relatively short travel distance of this urban corridor. Plots 43c and 43d show that platoon duration is slightly longer when trucks make up 20 percent of traffic due to the larger number of trucks in the stream, but still, duration largely remains less than 50 seconds.



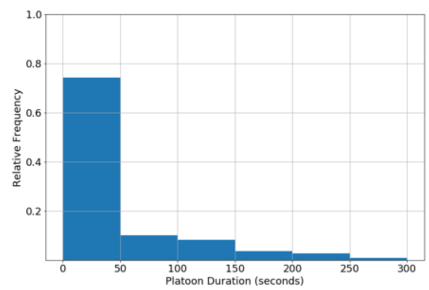
a) 10 percent trucks – low automation (30 percent AV).



b) 10 percent trucks – high automation (70 percent AV).



c) 20 percent trucks – low automation (30 percent AV).



d) 20 percent trucks – high automation (70 percent AV).

Figure 43. Truck platoon duration for 10 percent/20 percent trucks at low (30 percent) and high (70 percent) AV market penetration levels.

Chapter 11. Lessons Learned and Next Steps

This project report presents a comprehensive methodological framework for evaluating the strategic and operational impacts of CAV systems. The framework builds on the user needs and system requirements identified in previous tasks. The framework is comprised of four interdependent components:

- **Supply Changes**: to analyze the emergence of new mobility options enabled by CAVs and the changes incurred by the new technology to the infrastructure. This would mainly include 1) the emergence of new mobility options and 2) changes to the infrastructure to enable wireless telecommunications.
- **Demand Changes**: to evaluate CAV impacts on 1) activity patterns such as the sequencing of activities or vehicle ownership and 2) travel choices such as the mode of choice, route, and departure time.
- **Operational Performance**: to evaluate the impacts of the technology on the performance of transportation systems such as increased capacity and improved travel time. These sets of models would capture the new driving behaviors among CAV systems, the impact of wireless telecommunication and information flow, and the heterogeneous traffic interactions among the different behaviors and control systems.
- **Network Integration**: to capture the multi-agent interactions at the network level and integrate the demand, supply, and operational components.

As a first step toward developing the methodological framework, the study team conducted a comprehensive review of prior and current work. The review of supply-related impacts of CAVs into the traffic stream focused on the operation of shared-automated-vehicles (SAV) as a new mobility option that CAV technology makes possible. The main findings of the reviewed papers, which are still largely speculative, suggest that SAVs can reduce individual travel times compared to personal vehicles when fleet size is optimized and dynamic vehicle allocation is applied. Furthermore, the studies suggest that SAVs can replace multiple personally owned vehicles, but the optimal number depends on demand and system configuration. As for the AMS tools used in this area, recent developments are beginning to produce heuristics and simple strategies to operate and manage emerging mobility fleet services with CAVs; while the work is in the early stages, it is advancing rapidly as the involvement of researchers from different disciplines grows.

On the demand and behavioral change side, the reviewed papers suggest that adoption of the new technology will be gradual and that high market penetration is not likely before 2060. Such predictions must be taken with considerable caution, as they depend on many assumptions regarding market trends and industry offerings. Furthermore, early adopters of the technology will likely be young, educated, and affluent adults. In terms of mode shift, results suggest that the introduction of AVs will likely cause a shift from public transit and walking for short distance travel, and a shift from air travel for longer distances. As for vehicle ownership, SAV service can significantly reduce the number of vehicles owned if accepted by the public. With respect to VMT impacts, all results suggest that the new technology is likely to increase the total VMT due to the greater accessibility of the new mode. However, the extent to which VMT will increase differs among the studies due to the different assumptions about the operation and specifications of the CAV systems. As for AMS tool development to evaluate demand changes, existing integrated ABM-DTA structures are amenable to incorporate such CAV impacts, provided they are conceived as tour-based (rather than trip based), enable multi-class equilibration including system optimum for certain AV tours, and recognize user heterogeneity.

Regarding operational performance, the reviewed studies suggest that CAV systems have a positive impact on the stability and rate of traffic flow that is proportional to CAV market penetrations. Furthermore, the new technology can potentially improve traffic control algorithms such as speed harmonization. The topic of CAVs and their potential impact on traffic, mobility, and urban and regional systems has captured the attention of many researchers from all over the world. The number of studies on this topic has rapidly increased in recent years, as reflected in journal publications and conference presentations. Work to date has primarily helped to identify and frame the many complex issues that arise in evaluating the full impacts of this new technological paradigm as well as to point to some of the difficulties and limitations in modeling these impacts in a realistic and robust manner. Recent special-purpose model developments at the operational level are already providing considerable insight on various traffic operational aspects of mixed traffic with CAVs, although they do not provide a sufficient capability to support traffic control and design decisions. In terms of regional impacts, the use of microsimulation experiments to generate macroscopic relations (e.g., fundamental diagrams) for individual facilities, which may then be used in mesoscopic network simulation tools, provides a promising direction for quick-starting investigations of CAV impacts on a large regional network scale.

Building on the comprehensive review of prior and current work, a gap analysis of current CAV AMS capabilities was conducted. The analysis identified three types of gaps: methodological, data-related, and implementation-related. Methodological gaps involved key CAV system characteristics that were missing from most existing CAV AMS capabilities, such as an abstract representation of sensor performance or wireless telecommunications. Data-related gaps mainly involve the lack of actual data to calibrate and validate existing CAV models, such as the data required to validate the driving behavior of AVs designed to serve different purposes. Finally, implementation-related gaps mainly involved the integration of different framework components within a comprehensive CAV AMS system.

The developed CAV AMS framework addresses the identified gaps in different ways (*4*)(*4*)(*4*)(*4*)(*4*)(*4*):

- *Methodological gaps* were addressed by integrating the missing CAV-related features into the different components of the framework.
- *Data-related gaps* were addressed by allowing the different models in the CAV AMS system to be replaced/calibrated once new data becomes available.
- *Implementation gaps* were addressed by integrating the demand, supply, and operational performance models into a comprehensive framework of a CAV AMS platform.

Addressing most of these gaps, especially those related to data, requires field studies to be conducted (using prototype vehicles) to collect actual data on the behavior and interactions of CAV systems or analyzing data already collected in prior studies. Other options include using driving simulators or reaching out to private companies that are willing to share the data they already collected. The latter may not be an easy option since the private companies that are developing CAV systems are very protective of their data. Addressing methodological gaps mainly requires modifying existing models to include missing key CAV characteristics or building entirely new ones. Finally, addressing implementation-related gaps mainly requires building the CAV AMS system as a comprehensive modeling platform.

To conduct a proof-of-concept test of a prototype CAV AMS framework, a case study focusing on the operational performance impacts of CAV systems was selected. This case study focuses on the performance impacts of CAV systems in a mixed-traffic environment (i.e., CAVs, human drivers, and trucks) at different market penetration ratesof CV, AV, and CAV . The study uses an integrated traffic-telecommunication microsimulation tool that was developed at Northwestern University as a testbed. The microsimulation platform is a special-purpose tool for simulating mixed-traffic conditions on freeways in a connected environment. It integrates four distinctive driving behaviors: isolated-manual, connected-manual vehicles (CV), isolated-automated vehicles (AV), and connected-automated vehicle (CAV).

Using the aforementioned testbed, three sets of scenarios were evaluated. Those scenarios analyze the following:

- The performance of mixed traffic flow.
- The impact of AV sensor performance on mixed traffic flow.
- The impact of automated truck platooning on mixed traffic flow.

The mixed traffic flow simulations show that connectivity and automated driving can improve traffic flow throughput, stability, and travel time at high market penetration rates. The AV sensor performance simulations show that distance measurement error has insignificant impact on the performance of traffic flow in the case of the low AV market penetration rate. Automated truck platooning simulations show that active platooning can lead to higher traffic throughput due to trucks driving at shorter distances in platoons. Platooning, however, seems to have insignificant impact on the overall travel time. The truck platoons formed under the assumed opportunistic platoon formation strategy are small (2-4 vehicles) and of short duration (mostly less than 50 sec). Under the opportunistic strategy, connected trucks activate platooning behavior only if they are following other connected trucks. Due to the generally small number of trucks on highways (< 20 percent), forming platoons under this strategy can be difficult, especially in a short urban corridor.

Recommended Next Steps

The logical next step in this effort is to develop an AMS platform that builds on the methodological framework introduced in this project. While current AMS tools provide a step in the right direction in terms of evaluating CAV impacts, they primarily focus on one particular aspect of the potential impacts, such as operational impacts. CAV impacts, however, are far reaching on multiple levels, and evaluating those impacts requires an integrated approach at the network level. Such development is currently at an early stage, and much more work needs to be done in this area. Another area that is worth pursuing as a next step is collecting actual data to calibrate the different CAV-related models. On the demand side, for example, most models lack actual data that describes travel behavior changes among households due to the potential for allowing travelers to multitask while being transported by an AV. On the operational side, the data to support modeling the different driving behaviors of CAV systems and their interactions with human drivers or vulnerable road users is very limited. Collecting more representative data from actual site experiments would be essential to model CAV systems accurate and to evaluate CAV impacts.

The gaps identified and discussed in chapter 7 provide the list of critical areas for future work in the four key areas of demand, supply, operational performance, and network integration. Each one of these could be the basis of an extensive, full-fledged research program. However, agencies' need for AMS tools to help plan for the advent of CAVs in their communities are more immediate and need to be met with improvements to existing platforms using largely available data. Accordingly, the research team believes that one of the most productive areas for R&D is in studying how to address the demand and network-level aspects of CAVs. These are currently subject to the greatest uncertainty regarding adoption and use of the new technology and new services likely to be offered by third parties. While the framework addressed all aspects with the same general level of detail, the case study in chapters 9 and 10 focused almost exclusively on operational aspects. It would be highly desirable, and of prime interest to stakeholders and agencies, to conduct a similar case study that focuses on the demand and network impacts of new CAV technologies and related mobility services instead.

The location for such a case study would be a large urban or metropolitan network, and the research would address household adjustments based on CAV availability, both as household-controlled assets as well as in a mobility-as-service scenario based on shared-fleet options. More importantly, the case study would need to capture interactions among these various effects and examine implications in a network context, including multimodal travel options, particularly public transit services in the study area. The case study would also need to consider potential equity concerns across user groups as well as across various geographical areas.

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