Federal Highway Administration (FHWA) Connected and Automated Vehicles (CAV) Analysis, Modeling, and Simulation (AMS) Program

Future Effective Capacity: Assessing Traffic Flow Impacts for Variable Levels of Automation and Market Acceptance

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Rick Grahn, Claire Silverstein, Peiwei Wang, Karl Wunderlich	
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16. Abstract

Automated vehicle (AV) technologies promise numerous benefits to highway capacity and stability through improved reaction times and optimized decision-making processes. However, commercially available automated features (mostly at lower levels of automation) do not exhibit the same behaviors assumed in theoretical studies, which limits near-term benefits (or even causes efficiency to deteriorate) in many real-world operational conditions. These same discrepancies also lead to modeling errors when simulating diverse scenarios for capacity planning exercises. This analysis addresses these uncertainties by reviewing relevant literature with a specific focus on the optimistic and pessimistic viewpoints of AVs related to highway capacity and stability, with a focus on car-following and lane-changing behaviors. Gaps and challenges are identified that limit realistic modeling of AVs in mixed traffic. Potential future research directions are also presented that address specific AV modeling gaps for near- and mid-term operational planning.

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Executive Summary

The purpose of this document is to identify future research, data collection, and/or deployment activities that can help fill gaps in the microsimulation literature related to modeling automated vehicles (AV) and human drivers in realistic, near-term, mixed traffic environments. This analysis focuses on freeway efficiency because most automated vehicle technologies are primarily used on uninterrupted flow facilities. Additionally, limited data exists related to vehicle behaviors at different levels of automation on arterials. No connectivity between vehicles and infrastructure is also assumed because the widespread use of vehicle connectivity technologies is an unrealistic assumption for near-term planning. A thorough (though not exhaustive) literature review was conducted focused on 1) how AVs are theoretically modeled (and their associated assumptions), 2) identifying shortcomings of current modeling and simulation approaches, and 3) how assumed AV behaviors differ from real-world observations. For example, theoretical AV studies tend to assume overly optimistic headways and reaction times compared to observations from on-road testing of commercial adaptive cruise control (ACC) systems. These unrealistic assumptions about AV capabilities can lead to errors when modeling AV capacity impacts in the near-term.

This study breaks down the types of driving behaviors into two groups: 1) longitudinal control and 2) lateral control. Both types of behaviors impact freeway capacity, with the former receiving the most attention in the literature. Many new (commercially available) L1-L2+ automated features provide warnings, assistance, and/or automated control in both longitudinal and lateral directions. These new features also call for improved modeling approaches for AVs and human responses because they behave differently compared to human drivers. After reviewing both theoretical AV modeling/simulation research and real-world automated feature testing studies, the following gaps and challenges were identified, which can be grouped into three overall themes.

Theme #1 – Simplified, unrealistic modeling assumptions:

- Theoretical simulation studies assume perfect technology performance and limited impacts from human factors. These assumptions are overly optimistic and inaccurate in the near- to mid-term, which can impact capacity planning. For example, numerous studies found that commercially available ACC systems degraded performance due to longer reaction times, longer desired time headways, and greater instability, which contradicts findings from the theoretical, simulation-based literature.
- AV lane changing behaviors and the resulting responses from adjacent human driven vehicles are rarely considered in highway capacity simulation studies. This is partially due to the lack of understanding from limited empirical data.

- Most literature assumed homogeneous behavior for AVs. However, automated features have different capabilities (based on hardware/software stacks and levels of automation), controls, and risk attitudes (as programmed by the developer) that vary between OEMs.
- There is a lack of studies that consider realistic environments (non-ideal weather, road gradients, complex configurations), imperfect automation, and different vehicle types, including medium and heavy vehicles (which will rely on different hardware and control algorithms). The performance of AV features and human responses across diverse conditions will ultimately determine the costs and benefits of AVs operating in the real-world.

Theme #2 – Limited understanding of human-machine interactions and cooperation:

- There is a lack of research related to how human-machine interactions and cooperation within the vehicle for L1-L3 features will impact car-following and lane-changing behaviors, such as takeover events, transfer of control, and failover procedures.
- Initial studies found that human drivers will take advantage of AVs in certain conditions, which can impact safety and efficiency. Further research is needed to identify how human driving behaviors might change in the presence of AVs.

Theme #3 – New modeling frameworks needed to capture realistic AV behaviors:

- Traditional car-following and lane-changing approaches that model human behaviors are also being used to model AVs by modifying inputs related to reaction times and headways. This approach, while intuitive, does not capture AVs' underlying data-driven decision-making processes that include sensor inputs, data fusion, recognition, machine learning/AI, and optimized decision making.
- Assumptions about vehicle controllers are idealistic and do not consider different levels of automation with different hardware/software capabilities (standard ACC algorithms are primarily used in research). Controls will also vary based on conditions (e.g., road gradients) and vehicle types, which is an area with limited research.
- There is limited understanding related to AV lane changing behaviors (e.g., trajectories, risk attitudes, execution), which are based on sensor inputs and data-driven decision making.
- There is a lack of studies assessing highway capacity improvements due to increased safety provided by AVs (e.g., smoother trajectories, reduced speed variance).

Future Research:

- Most theoretical simulation studies assume ideal conditions, simplified environments, high levels of technology performance, simplified lateral behaviors, and homogeneous capabilities for all AVs within the traffic stream. These assumptions are overly optimistic for near-term modeling and operational planning. Therefore, there is a need to study how AV technologies and driver settings preferences/modified behaviors (e.g., minimum gaps, lane change frequency when using different automated features) impact operations across a wide range of real-world environments (e.g., weather, lighting, road geometry).
- The popularity of hands-free automated features (L2+/L3) has grown in recent years due to more advanced automated controls capable of easing driving tasks. Such systems require more complex human-machine interactions to switch control. Additionally, the roadway capacity impacts resulting from commercially available L3 failover protocols (the procedures

vehicles follow when a driver is unable to takeover in a reasonable amount of time) are not well understood. Therefore, there is a need to study human-machine interactions for hands-free systems available today (L2+/L3) and the impacts of different failover procedures along with their frequency of occurrence.

- AV and human decision-making processes are fundamentally different, which calls for new methods and frameworks to model and simulate these two sets of behaviors simultaneously. The most widespread approach to modeling AVs (to date) is to modify input parameters previously developed for human drivers. However, this approach does not capture the underlying AV decision-making process, which can limit future modeling enhancements and applications. Therefore, there is a need to develop and incorporate AI-based decision-making processes into current traffic modeling and simulation tools.
- The average roadway capacity can be significantly impacted by collisions, which is another area that AVs can positively contribute in terms of mitigation/prevention. To date, few studies have made the connection between safety improvements and capacity impacts, which leads to the need for further research to accurately assess AV impacts on highway capacity.

1 Introduction

Automated vehicles (AV) offer many advantages over human drivers due to their ability to collect and process large amounts of data to inform near-instantaneous actions. This capability translates to faster reaction times and improved real-time decision making (e.g., braking, accelerations, and/or maneuvers to avoid a potential collision). These improved reaction times and choices can also lead to network efficiency gains without increasing collision risk through closer following distances and smaller required gaps for lane changes. Many theoretical studies have shown efficiency improvements through simulation when assuming shorter following distances and smoother accelerations/decelerations. However, these studies are almost exclusively conducted using idealized conditions (e.g., perfect weather, no road gradients, perfect technology performance), which may not be realistic for all levels of automation (Society of Automotive Engineers [SAE] L1-L5) in highly variable real-world conditions. Additionally, it is unclear to the extent efficiency can be improved (or degraded) with different automation technologies (with varying capabilities) at different levels of market penetration. This comprehensive (though not exhaustive) review summarizes the current literature related to how automation technologies can impact freeway efficiency. This analysis focuses on freeway efficiency because most automated vehicle technologies are primarily used on uninterrupted flow facilities and limited data exists for AVs on arterials. No connectivity between vehicles and infrastructure is also assumed because the widespread use of vehicle connectivity technologies is an unrealistic assumption for near-term planning. Specific attention is paid to the assumptions made in the literature to identify gaps that may contribute to discrepancies between theoretical research and real-world conditions and/or observations. The efficiency impacts over time as penetration rates increase and connectivity technologies mature and become more widespread, are also explored to help inform near- and medium-term operational planning. Finally, recommendations are provided to help advance methods and improve guidance related to modeling AVs across a variety of real-world scenarios.

1.1 Efficiency Impacts from Automated Vehicles

Vehicle throughput is the most common way to measure the efficiency performance of a freeway facility and is calculated by summing the number of distinct vehicles (or other road users/people) that enter and exit the system during a specific analysis period. Different driving behaviors affect system throughput in various ways and can be grouped into two distinct categories: 1) longitudinal behaviors and 2) lateral behaviors. Longitudinal behaviors are defined by acceleration, travel speeds, and/or car following habits. Lateral behaviors are defined by the type of lane change (mandatory or discretionary), gap acceptance (is there a sufficient gap to safety execute a lane change?), and lateral trajectories (how the lane change is executed). Shorter average time gaps and higher average travel speeds lead to increased throughput up to the point when the system becomes unstable (i.e., gaps are too short and/or speeds are too fast for humans to avoid collisions and/or prevent traffic oscillations). Therefore, efficiency and safety/stability tradeoffs must be considered to maximize overall system performance. In summary, average time headways, travel speeds, and lane changing behaviors that include gap acceptance and lane changing frequency all impact highway throughput. To model highway capacity impacts, input parameters that define these longitudinal and lateral behaviors for human drivers are determined based on risk attitudes (e.g., risk adverse versus risk seeking). Similarly, automated vehicles (AV) can be modeling by modifying these same input parameters to capture vehicle control system behaviors and automated decision making.

AV features can shorten driver reaction times because they can process more data from numerous sensors and output optimized complex decisions faster than human drivers in most cases. Additionally, reaction times are consistently lower because AV systems do not become distracted. Vehicles controlled by algorithms are also more consistent and predictable compared to human drivers, which improves traffic stability by maintaining consistent speeds and reacting earlier and more predictably to incidents and events. The ability for AVs to smooth traffic flows (when penetrations levels are sufficient) also reduces the variation in travel speeds, resulting in improved stability. AVs also enable more precise, and potentially smoother lane changes because they utilize a vast array of sensors (radar, lidar, cameras) for improved awareness and understanding of real-time conditions. In summary, AVs can (in theory) reduce headways, increase travel speeds, and smooth trajectories (both longitudinally and laterally), all of which contribute to improved throughput without compromising safety. This is due to shorter reaction times, improved real-time decision making, and advanced vehicle controls that produce consistent and smooth driving profiles.

Real-world testing of commercially available automated systems has primarily focused on adaptive cruise control (ACC), which is a feature that uses sensors and speed controls to automatically manage the gap between target and subject vehicles. This capability eases the longitudinal driving burden for human drivers, which can alter longitudinal behaviors (e.g., fewer lane changes, automatic controls react differently compared to human drivers). Early findings analyzing the longitudinal behavior of commercial ACC systems contradict both the assumptions commonly used to model/simulate AV car-following behaviors (shorter time gaps and reduced reaction times) and their resulting impacts to throughput for the following reasons. First, manufacturer configurable headway settings and human preferences for desired time gaps do not align with theoretical assumptions. Next, current ACC control systems (without connectivity) react slower compared to humans when responding to leading vehicle perturbations. Third, the shift in liability for higher levels of automation (L3-L5) will likely result in more conservative time headways and gap acceptance settings to ensure safety, especially during early AV deployments. Finally, AV performance deteriorates when subjected to real-world conditions (e.g., adverse weather, wind, winding roads, steep roadway gradients); however, the extent of deterioration is not well understood. For these reasons, AVs could degrade highway capacities in many real-world settings in the near- to mid-term.

From a lateral movement perspective (e.g., lane changing), studies that use real-world data to study AV lane change and adjacent vehicle behaviors are limited. Most theoretical AV studies analyzing highway capacity impacts simply do not consider lane changing behaviors due to the limited knowledge of AV lane changing behaviors [1]. However, the release of new data (e.g., Waymo Open Dataset[1]) has motivated and made possible new research in this area, which can be used to improve modeling approaches for AVs in highway settings. For example, Wen, et al. [2] found that AVs exhibited improved lateral and longitudinal stability during lane changes, which reduces occurrences of traffic oscillations. Ali, et al. [3] came to similar conclusions; however, they also found that AVs maintained larger lead and lag gaps and took longer to execute lane changes compared to human drivers. These findings highlight the need to consider lateral behaviors because they can impact both traffic stability and average time headways.

1.2 Purpose

The purpose of this document is to identify future research, data collection, and/or deployment activities that can help fill gaps in the literature related to modeling AVs and human drivers in realistic, mixed traffic environments. A specific focus will be placed on how input parameters for both AVs and human drivers can be varied to model a wide range of real-world operational scenarios over the next 10 years. The overarching goal is to advise future research directions based on gaps/challenges identified in the literature related to the limitations of current AV modeling approaches for near-term capacity assessment and operational planning.

1.3 Scope of Document

This document focuses on automated vehicle (SAE L1-L5) impacts on freeway efficiency not considering connectivity. Potential added benefits of connectivity technologies will be briefly discussed. Gaps related to modeling AVs in near-term, real-world conditions will be identified to motivate future research directions to bridge AV modeling research and practice. Current best practices related to input parameter selection across various operational scenarios will also be presented. Microsimulation behaviors in both longitudinal and lateral directions are the primary focus of this analysis.

[1] https://waymo.com/open/

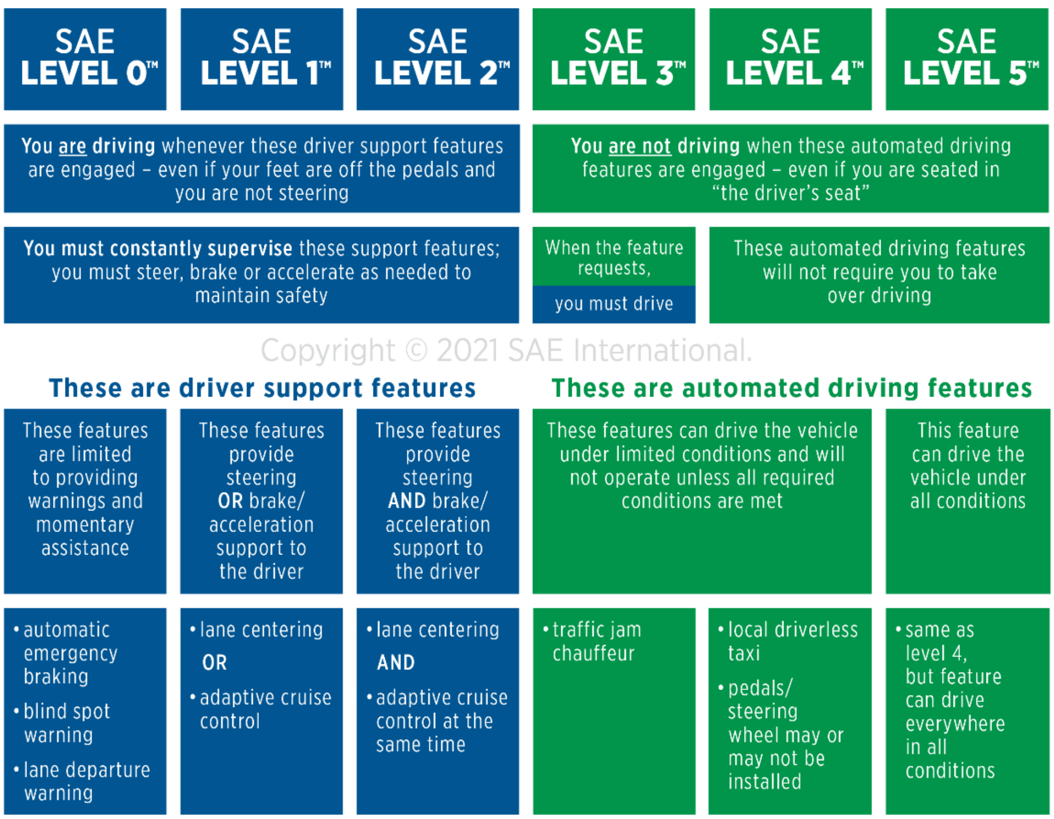
1.4 Report Organization

The remainder of this white paper is organized as follows:

- Chapter 2 defines the various levels of automation and their capabilities, provides a summary on modeling and simulation approaches for AVs, and summarizes the current literature related to AVs impacts on highway efficiency (theoretical and through real-world testing) and string stability.
- Chapter 3 summarizes the current state of AV technologies and aggregates reports and literature related to AV and connectivity technology development and deployment projections.
- Chapter 4 summarizes the findings from earlier research and identifies future research directions that target the identified gaps and challenges.

2 Literature Review

There is a long list of automated features that are currently being developed and deployed in commercial vehicles today because 1) different features vary in capabilities/use cases and 2) automotive manufacturers define these features in different ways for marketing purposes (e.g., “Smart Cruise Control”, “Dynamic Radar Cruise Control”, and “Distronic Plus” are all names for Adaptive Cruise Control from different auto manufacturers [4]. However, this long list can be distilled down to a couple of key features that automate vehicle control *longitudinally* and/or *laterally*. The six associated levels of automation defined by the Society of Automotive Engineers (SAE) J3016 [SAE J3016] also help group these features (or feature bundles) in terms of capabilities and driver responsibilities (see **Figure 1** for details).



Source: SAE J3016

Figure 1 - SAE Definitions and Applications for Various Levels of Automation (L0-L5)

2.1 Automated Features

This section defines these technologies in terms of direction of control (longitudinal or lateral) and style of automated control (momentary assistance, automated control) since traffic efficiency and throughput impacts depend on both categories of factors.

Longitudinal Controls:

Warnings/momentary assistance: These features are designed to promote safer driving behavior and/or momentarily intervene in specific situations to avoid an imminent dangerous situation (e.g., a collision). Examples of such features include automatic emergency braking and forward collision warning.

Automated control: These features provide braking/acceleration support. Cruise control takes speed signals from a rotating drive shaft and maintains the desired speed by pulling the throttle cable. Adaptive cruise control (ACC) maintains and automatically adjusts vehicle speeds to maintain a safe distance gap to the leading vehicle. Different ACC systems use different types of on-board sensors (e.g., laser-based systems, cameras, radars) to monitor the distance to the leading vehicle. In terms of effectiveness, one study found that camera-based systems had shorter following distances compared to radar-based systems in real-world testing [link]. However, system settings will also vary between manufacturers. Cooperative Adaptive Cruise Control (CACC) is adaptive cruise control with vehicle-to-vehicle (V2V) connectivity that allows leading vehicles to communicate position, velocity, acceleration/deceleration, and direction of travel to upstream vehicles (including vehicles outside of sensor line of sight) at regular intervals (usually at 10Hz). These high-frequency communications reduce reaction times for all upstream vehicles, which is different from ACC, where each following vehicle only reacts to disturbances within sensor line of sight (i.e., from its immediate leading vehicle). For example, when CACC is used, information about an impending acceleration/deceleration from the first vehicle (leader) is passed to all following vehicles within range (typically up to 1,000m). This quick and frequent transfer of information to all upstream vehicles within range allows for proactive speed adjustments to ensure string stability, rather than reactive controls based on limited information (e.g., leading vehicle only). Additionally, quicker reaction times allow for shorter (safe) following distances and increased throughput. Vehicle platooning is a similar concept to CACC, and it uses similar technologies and controls to maintain safe following distances between leading and following vehicles. However, due to the differences in platooning goals, cooperative decision-making processes, and operating conditions, the two terms (platooning and CACC) are not interchangeable. Platoons use V2V communications to minimize spacing between vehicles to improve fuel efficiency on freeways. All vehicles in the platoon cooperate centrally to achieve the desired efficiency improvements. CACC, on the other hand, uses V2V to maintain safe gaps between vehicles to help improve safety, smooth traffic flows, and increase longitudinal stability. Each vehicle employing CACC undergoes an independent decision-making process based on the information provided from downstream vehicles to maximize safety and stability. Vehicle platooning applications are not the focus of this paper due to their narrow scope and limited near-term impacts on general freeway throughput.

Lateral Controls:

Warnings/momentary assistance: These features provide warnings/alerts to drivers when the vehicle is veering outside of the lane or to aid the driver when making lane changes (e.g., blind spot warning). Lane departure warning systems often use camera-based vision sensors to monitor lane markings and alert the driver when the vehicle is leaving the lane using visual cues, auditory warnings, and/or tactile vibrations [Lane Departure Warning Definition]. Lane Change Assist uses sensors (radar + cameras) to monitor approaching vehicles in adjacent lanes and provides warnings to the driver to prevent dangerous lane changes [Lane Change Assist Definition]. The sensors/warning systems are only engaged when a driver indicates that they wish to change lanes (e.g., activating a turn signal). The term "assist" in this context refers to providing extra visibility to the driver using on-board sensors.

Lane keeping/lane centering: These features continuously monitor lane markings and automatically adjust direction of travel to keep the vehicle from departing the lane. Lane keeping assist/lane centering is a common feature that performs this task using camera-based visual sensors to monitor lane markings. The capabilities of lane keeping/centering features depend on on-board sensors, lane markings, and algorithms that are used to detect lane boundaries and subsequently adjust vehicle trajectories [link]. Therefore, the technology maturity is manufacturer dependent. In addition, it is common for lane changing/centering features to disengage when sharp curves (or even moderate curves when speeds are high) are present. When coupled with high-definition maps, lane keeping/centering features improve their performance by communicating upcoming curves to onboard systems. This is important because constraints related to sensor range, poor road markings, and algorithm speeds can be overcome using upcoming roadway information.

Automatic lane changing: These features perform automated lane changes when the driver indicates the desire to change lanes (i.e., using the turn signal). When initiated, the feature assesses surrounding traffic conditions, checks blind spots, and executes the lane change if conditions are safe. If conditions are not safe, the vehicle searches and identifies a safe gap prior to executing the lane change. Cooperative lane changing, which is more advanced compared to standard automatic lane changing features, uses V2V and vehicle-to-infrastructure (V2I) to facilitate smoother lane changes through data sharing and cooperation. A vehicle looking to change lanes shares its intentions with nearby vehicles and infrastructure. Adjacent vehicles then adjust their speeds to create a safe gap for the lane change. Infrastructure components also communicate optimal lane change timing based on current conditions.

Autonomous lane changing: These features make lane changing decisions and execute lane changes without driver intervention. Lane changing decisions are based on current road conditions, traffic flows, and the vehicle's routing information. Autonomous lane changing is mostly reserved to higher levels of automation; however, some lower levels (e.g., L2+) exhibit these capabilities on pre-mapped roadways.

2.2 Traffic Simulation Approaches

Modeling and simulation tools are cost-effective ways to quantify the impacts of emerging transportation technologies on traffic flow across a wide range of potential scenarios. When it comes to evaluating freeway efficiency impacts, there tends to be three general approaches depending on the research objectives and resolution of impacts that are desired. First, *microsimulation* models simulate individual vehicle movements using car-following and lane-changing theories. These simulation models are generally constrained to small areas because they require large amounts of data and significant computational resources, making them time intensive and expensive to implement. *Macroscopic* models, on the other hand, simulate more aggregate, network-level traffic based on relationships between speed, flow, and density of the traffic stream along various links. These models are cheaper and quicker to run and provide high-level results when network or corridor level impacts are sought. *Mesoscopic* models fall somewhere in between in terms of complexity and fidelity. *Mesoscopic* models typically simulate traffic flows at the vehicle level; however, vehicle trajectories are determined by link travel speeds (as opposed to more detailed car-following or lane-changing models). These models can simulate corridors with higher accuracy and lower computational burden compared to macro- and microscopic models, respectively. Ultimately, the three modeling approaches were developed to answer different questions at different levels of resolution.

In addition to these three approaches, deterministic methods can also be used to estimate capacity impacts. The Highway Capacity Manual (HCM) is one such example that integrates the latest research into a consistent set of methods for practitioners to evaluate highway capacity and level of service. The 7th edition HCM is the first to consider the potential impacts of connected and automated vehicles (CAV) on freeway capacity. As defined by the HCM, AVs can perceive their surroundings to make decisions with little human intervention, and CVs can transmit information wirelessly between vehicles, infrastructure, and pedestrians. CAVs combine automation and connectivity for improved operations and cooperation. To model the impacts of CAVs on freeway capacity (and to derive capacity adjustment factors for the HCM), three base models were developed (2-lane freeway, 2-lane freeway with merge, and 2-lane freeway with weaving segment) using VISSIM's built-in driver behavior models (Wiedemann99). CAVs were then introduced using CACC logic (gap-regulation controller) developed by Milanes & Shladover [5] for longitudinal controls. For lateral movements, the Advanced Merging algorithm adapted from VISSIM 11 was used to cooperatively merge/weave using V2V and V2I technologies [6]. Discretionary lane changing behaviors were not considered. The three scenarios were then simulated using microsimulation software (VISSIM) to determine appropriate capacity adjustment factors (CAF) under various assumptions (e.g., intra-platoon gaps of 0.6s, 1.1s, and normal distribution; maximum platoon length of 10 vehicles) and market penetration rates of CAVs (0.2, 0.4, 0.6, 0.8, 1.0). CAFs are multipliers that are used to adjust base capacity levels due to weather, incidents, work zones, or the presence of CAVs [6]. More detailed information about the CACC algorithm used for the HCM analysis can be found in Schroeder [6]. In this paper, HCM methods are only briefly presented because the connectivity assumption is out of scope for this analysis.

In terms of modeling AVs, *microsimulation* has been the primary focus area because significant uncertainty still exists in terms of individual AV behaviors and insights can still be gathered when AV penetration rates are low [7]. The following section provides further details regarding each of the modeling approaches.

Microscopic Simulation

Car-following: Theoretical car-following models have been used since the early 1950's to describe traffic phenomena. These models generally fall into three main categories based on the approach used to describe the car-following characteristics [8][2]:

- Kinematic models – focus on vehicle motion and dynamics.
- Psycho-Physical (or Action Point) models – physics-based models that integrate human perception and decision making.
- Adaptive Cruise Control (ACC) models – focus on maintaining a safe gap between vehicles using low-level controls.

Numerous model formulations and extensions have been proposed for each of these model types that require different inputs and assumptions. The most popular kinematic models are Safe Distance (or Collision Avoidance) models [e.g., Newell's Model, Gipps' Model], Optimal Velocity models, Desired Measure models [e.g., Intelligent Driver Model], and Stimulus-Response models. Safe distance models focus on maintaining sufficient space between leading and following vehicles. Optimal velocity models assume that vehicles pursue an optimal velocity through acceleration and braking that is dependent on the headway distance. Desired measure models assume that vehicles pursue optimal speeds and headways, simultaneously. Psycho-Physical models consider human attentiveness and perception, where behaviors change based on traffic conditions (e.g., free flow, congested). Popular psychophysical models developed by Wiedemann—Wiedemann 74 [9] and Wiedemann 99 [10]—define different following behaviors for the four traffic regimes: 1) free flow, 2) approaching, 3) following, and 4) emergency [11]. Weidemann 74 and Wiedemann 99 only vary in the thresholds that are used to distinguish between urban and freeway driving behaviors. Finally, ACC models use low-level controls to modify vehicle speeds through acceleration/braking based on the desired gap from the leading vehicle. ACC algorithms can also be used to improve traffic stability by smoothing acceleration/deceleration rates. Generally, ACC car following models are not used to simulate

[2] The three groupings do not represent all possible microsimulation approaches and were selected as part of this review due to their prevalence in the AV microsimulation literature.

human drivers because of the computational complexity required to estimate higher order derivatives [12].

The complexity of today's transportation system (heterogenous users, vehicles, varying road conditions, etc.) creates challenges for the parametric modeling approaches discussed above. At the same time, driving behavior and other transportation-related data has become more readily available and has opened the door for data-driven models, which outperform analytical models in complex scenarios [8]. Machine learning (ML) and/or deep learning approaches have been used to model car-following behaviors using trajectory data. This approach is anticipated to become more relevant when modeling AVs because of their reliance of artificial intelligence (AI)-based algorithms [12].

Lane-changing: Lane changing models are generating increased interest in recent years due to potential impacts on traffic safety and efficiency [12]. Like car-following, lane changing models use both parametric and data-driven approaches, with the latter garnering increased attention with advances in data collection, algorithms, and machine learning. The earliest lane changing models were based on a set of rules that first determines if the lane change is mandatory (e.g., lane blocked, required to get to destination) or discretionary (e.g., move around a slow-moving vehicle). Then rule-based logic is used to quantify individual costs and benefits of the impending lane change (e.g., move around a lane blockage, increase travel speeds). Finally, a check is made to ensure that there is sufficient gap to execute the lane change safely. The Gipps model [13] is an early example of this approach. The majority of theoretical lane changing models follow similar logic that first classify the type of lane change (mandatory or discretionary), then use gap acceptance models to determine if the lane change should be executed based on the "critical gap" (i.e., smallest acceptable gap to perform a lane change safety) [14]. These types of decision models are broad and include numerous different approaches that include discrete choice, decision trees, utility theory, and game theory, among others [12]. Statistical models, on the other hand, leverage machine learning to predict/execute lane change maneuvers based on driving data. The machine learning approaches have been proven to perform well in complex, real-world situations (e.g., congested traffic) but lack interpretability and often require location-specific training [12]. In general, lane-changing models are not well understood compared to car-following models because the decision-making process is more complex and there is a lack of empirical data [15]. This lack of knowledge has limited the number of AV-related highway capacity impact studies that consider lane-changing behaviors [1].

In terms of modeling AVs, most of the reviewed studies followed three general approaches: 1) modifying tool parameters using built-in models (e.g., VISSIM, AIMSUN), 2) using tool built-in models with APIs for modelers to program their own AV logic that can override built-in logic, and 3) using co-simulation environments where AVs and traffic simulations can be coupled [1]. Most existing research leverages tools with built-in models and modified parameters based on simplified assumptions (e.g., shorter time headways to account for quicker reaction times). AV lane changing behaviors and subsequent lateral trajectories were rarely considered [1]. A detailed summary of AV assumptions and associated software tools can be viewed in Raju & Farah [1].

Macroscopic Simulation

Macroscopic models use mathematical relationships between speed, density, and flow to simulate network and regional traffic performance under various conditions to inform strategic planning decisions. In most cases, macroscopic models treat traffic as if it behaves like a fluid or gas, allowing aggregate flows to be modeled over a continuous space. Network-level origin-destination demand (which is either estimated or collected from roadway sensors) and a routable network is used to determine link-level demand based on individual travel cost minimization. Fundamental diagrams of traffic flow are then used to define speed, density, and flow relationships based on network conditions. Corridor/network-level impacts, such as instability (traveling waves), total delays, and impacts from collisions/incidents, can be derived using macroscopic modeling frameworks. Macroscopic approaches are also preferred when traffic data are limited, or when the data cannot be resolved at the individual vehicle level. Examples of macroscopic approaches include the Cell Transmission Model [16], the generalized Aw-Rascle-Zhang model [17, 18], and the full velocity difference model [19], which all serve as theoretical frameworks that have been enhanced and/or improved in recent years to incorporate emerging technologies and answer specific research questions.

For modeling AVs, the general approach is to modify the fundamental diagram based on assumptions about average headways. The consensus among researchers is that average headways will decrease with increased AV penetration, which will increase the critical flow density, and the overall lane capacity compared to human drivers [12]. These shifted fundamental diagrams (higher critical flow density paired with higher maximum flow rates) can then be used to simulate network-level impacts. It is important to note that uniform AV assumptions must be used, and that macroscopic models do not consider lateral movements (e.g., lane changes).

Mesoscopic Simulation

Mesoscopic models fall somewhere in between microscopic and macroscopic models and aim to balance fidelity and computational resources. Like macroscopic models, a routable network with origin-destination demand at the boundaries is often used to simulate traffic flows throughout the region/corridor based on travel cost minimization. However, the area under consideration is much smaller in scope (e.g., neighborhood, corridor). Like microsimulation, individual vehicles are modeled across links to capture interactions and dynamic traffic effects. However, the models that define traffic movements are more aggregate in nature. For example, vehicle movements across links are usually defined using speed/flow/capacity relationships, or link performance functions, as opposed to implementing car-following and/or lane-changing theories. These models serve as a nice balance between macroscopic and microscopic approaches when corridor-level impacts are desired.

Examples of mesoscopic approaches include the CONTRAM Dynamic Traffic Assignment model [20], DynaMIT [21], DYNASMART [22], cellular automata model [23], among others. The CONTRAM model groups vehicles into “packets” much like communications networks and uses link-level speed-density relationships to estimate flows. DynaMIT groups vehicles into cells that define vehicle behaviors. Cells move through links based on speed-density relationships, and vehicles can enter/exit cells but not overtake. DYNASMART uses a queue server approach where individual lanes and vehicles are modeled, and vehicles are transferred to connecting roads based on queueing theory. The cellular automata model discretizes the road into cells and each cell can either be occupied by a vehicle or empty. Braking time, accelerations, and vehicle type can also be defined at the cell-level. This approach allows for users to define cell size based on the level of detail and computational resources. In recent years, many of these approaches have been enhanced and/or modified by researchers, practitioners, and software developers to more accurately capture network conditions, emerging technologies, and new travel behaviors. For example, a widely used open-source tool call MATSim uses a computationally efficient, queue-based approach to model large-scale networks [24].

Mesoscopic models are important for evaluating traffic efficiency impacts of AVs because vehicle-level assumptions and characteristics can be used to evaluate corridor-level impacts across a wide range of scenarios. However, general assumptions are still needed regarding AV headways and travel speeds, which may require sufficient AV penetration to produce accurate results. Currently, the general assumption amongst AV modelers and researchers is that control systems deployed in AVs will reduce reaction times, which will enable closer following distances and improved stability and efficiency [25]. These assumptions can be integrated with mesoscopic modeling approaches by developing link models that implement smaller following distances for AVs.

Summary of modeling approaches

Significant uncertainty remains about how AVs interact and behave at the microscopic level, which limits the ability for meso- and macroscopic models to accurately represent AVs with simple and generalized assumptions. In addition, the aggregate nature of meso- and macroscopic models will struggle to accurately capture real-world conditions in the near-term due to low AV penetration rates. For these reasons, and the importance of resolving heterogenous behaviors at the vehicle level, this paper will primarily focus on the current state of AV microsimulation modeling methods, simulation, and assumptions.

2.3 AV Impacts on Highway Capacity

Most car-following and lane-changing models are based on exogenous rules and mechanisms fit to empirical data to capture human behaviors. This approach makes it difficult to capture the vast heterogeneity present in driving behaviors amongst the driving population, which is a drawback for most microsimulation frameworks. However, the assumption that AVs will behave similarly (with less heterogeneity) based on a set of programmed rules makes many of the classical microsimulation methods more appropriate for AVs [26]. Currently, the most common approach to integrating AV behaviors into traffic simulation models is to use already established car-following and lane-changing models developed for human drivers and appropriately modify the input parameters to better capture AV behaviors [1]. At the same time, this approach has some drawbacks when modeling AVs because it doesn’t capture the fundamental decision-making process of AVs (sensor data → recognition → decision → action or end-to-end AI), which is an algorithmic approach that takes in sensor data as inputs, then uses AI/machine learning to process the data and inform future decisions [12]. As mentioned previously, classical microsimulation theories also struggle to capture the significant heterogeneity and stochasticity present within the driving population. This same challenge is present when modeling AVs (perhaps to a lesser degree) because driving features have different capabilities (e.g., levels of automation, technology), programmed risk attitudes, and driver settings (e.g., what headways will drivers select to use for automated features?), which adds a new type of heterogeneity to consider in mixed traffic environments. To help bridge these gaps in microsimulation modeling, Calvert & van Arem [26] recommend the following to be considered when modeling mixed traffic situations (see **Table 1**).

Table 1 - Recommended Considerations for Microsimulation in Mixed Traffic Environments using Three Different Design Drivers (Human, L1-L2, L3-L5)

Type of driver	Recommendations
Human	• Real human driving dynamics • Human reaction to AVs
SAE L1-L2 (partial automation)	• Reduced driver awareness when in “monitoring” state • Endogenous human reaction modeling when taking over control (cognitive loading) • Human/AV interaction consequences
SAE L3-L5 (high automation)	• AV driving dynamics and rules • Driving dynamics for AV-to-AV interactions • Additional driving dynamics with connectivity

The most common modeling approach when evaluating highway capacity changes from AVs is to reduce the desired time gaps for AVs compared to human drivers. Based on the literature reviewed, the desired time gaps often used for AVs were between 0.7-1.4s compared to 1.4-2.0s for human drivers [15, 27]. In Heaslip, et al. [27], nearly all reviewed studies found improved highway capacity for AVs when desired time gaps were reduced for ACC vehicles. For AVs, Talebpour & Mahmassani [28] found that throughput could be increased to 2,500 veh/hr/ln at 90% AV market penetration. Carrone, et al. [29] assumed instantaneous reaction times for a homogeneous fleet of AVs (compared to 1s for humans) and time gaps of 1s and 1.3s for AVs and human driven vehicles, respectively. The study found that AVs increased throughput by 8%, 14%, and 30% for AV penetration rates of 50%, 75%, and 100%, respectively. Fan & Liu [30] assumed time headways of 0.9s and 1.2s for AVs and human drivers, respectively, and found that AVs increased freeway capacity by 20% at 100% market penetration. Mohammed & Horvath [31] conducted an extensive literature review related to microsimulation of AVs and found that nearly all studies concluded that AVs would increase highway capacity when market penetration rates reached some critical value that was dependent on modeling methods and associated assumptions. However, the critical market penetration rates ranged from 20%-70% [1], which makes operational planning difficult based on the large degree of uncertainty. Raju & Farah [1] reviewed more than 1,000 AV-focused microsimulation studies and found that capacity improvements were consistently observed when market penetration rates were greater than 30%. When penetration rates were below this threshold, lane capacity either did not improve or deteriorated slightly compared to 100% human driver base case scenario. These theoretical capacity improvements make sense because lane capacity is inversely related to the average time headways between vehicles.

As highlighted above, highway capacity calculations are dependent on average time headways. And while lane changing behaviors do not impact car-following directly, they do affect the system's average time headways because additional space is needed between vehicles to execute a lane change. In addition, lane changes often require accelerations/decelerations by nearby drivers (AVs or humans) to create acceptable gaps, which increases system heterogeneity and reduces overall capacity [15]. For these reasons, lane changing behaviors for AVs must be considered to generate accurate results. However, while AV lane changing models and methods have become popular areas for research in recent years [12, 31], their impacts on highway capacity are not well understood [1, 32]. In fact, most studies evaluating the impact of AVs on traffic flow neglect lane changing behaviors due to limited knowledge about how AV lane changing differs from that of human drivers [12]. Li & Wagner [32] used the default Erdmann lane changing model [33] in conjunction with the Krauss car-following model to simulate mixed traffic scenarios using the Simulation for Urban Mobility (SUMO)[3] tool. The "willingness to cooperate" variable was increased to 0.99 for AVs compared to 0.7 of human vehicles (scale from 0-1) based on the assumption that AVs will cooperate more with vehicle-to-vehicle (V2V) connectivity. The study found that in heavily congestion conditions, 100% AV penetration can increase throughput by 83%. However, the improvements attributed specifically to cooperative lane changing behavior were not analyzed. In recent years, new machine learning-based trajectory and control theory models are becoming more popular to optimize AV lane changing trajectories. These models typically use simulated data to optimize trajectories for safety and efficiency rather than using naturalistic driving data to calibrate human driver models [12]. Most of these studies also assume connectivity and cooperation, which are capabilities that are not expected in the near- to mid-term.

For highway capacity impact analysis in mixed-traffic environments without connectivity, different (new) behaviors must be captured and integrated into modeling frameworks for realistic

[3] https://sumo.dlr.de/docs/index.html

results. For example, human driving behaviors in response to AVs changing lanes likely differ compared to if a human was making a lane changing maneuver. Additionally, different AV developers use different technologies (e.g., cameras, radar, lidar) and settings (e.g., lead/lag gap, time headway), which may lead to different AV lane changing behaviors. Both AV and human driver response to AV driving behaviors are critical to include for accurate near- to mid-term operational planning. However, studies that consider these factors are limited due to the lack of automated lane changing technologies in operation. However, few studies have used recently released AV datasets, such as the Waymo Open Dataset, to evaluate human behaviors in response to AVs. For example, Wen, et al. [2] analyzed Waymo data and found that human driven following vehicles in an AVs target lane after a discretionary lane change exhibited improved lateral and longitudinal stability. In other words, the smoother, more predictable lane change from an AV caused less speed and yaw volatility for the following vehicle in the target lane. Ali, et al. [3] came to similar conclusions using the same dataset in that AV lane changing behaviors exhibited less heterogeneity compared to human drivers. The study also found that AVs maintained larger lead and lag gaps, took longer to execute lane changes, and had lower acceleration variation compared to human drivers. These findings indicate that AVs exhibit smoother lane changing behaviors (in some conditions), but at the same time, require larger gaps to execute a lane change, which can have varying impacts on highway capacity. It is important to note that these findings were based on Waymo L4 vehicles, which have different settings and behaviors compared to other automated vehicle features (L2/L3) developed by other manufacturers.

In summary, the classical models used to predict car-following behavior for human drivers can be well-suited for AVs because longitudinal behavior is ultimately constrained by system dynamics [26]. However, these models are still limited in their approach because they do not model the underlying AV decision making process. Most existing literature still use classical models and modify parameters to evaluate throughput at different levels of AV penetration. Inputs related to reaction times and desired time headways/gaps are often assumed to be lower compared to human drivers since AVs can process incoming data and make decisions faster than human drivers. These assumptions have led to anticipated outcomes of improved lane capacities when penetration rates are greater than 20-40% [1, 15, 34]. The critical time headway threshold that governs whether AVs will improve or degrade system performance at lower penetration levels was found to be approximately 1.2-1.5s [15, 35]. In terms of operating assumptions, most previous literature has focused on single lane, longitudinal capacity studies [32]. However, as AV modeling becomes more critical for operational planning in the near- to mid-term, new models that leverage both classical microsimulation theory and AI/ML are becoming more popular. In terms of commercially available software to model mixed traffic conditions, Raju & Farah [1] provided a comprehensive overview of modeling approaches and various assumptions used by different researchers. Currently, VISSIM is the most popular tool used in AV microsimulation. Table 3, in Raju & Farah [1], provides a detailed overview of the assumptions used by previous researchers to model AVs for the different microsimulation platforms (e.g., VISSIM, SUMO, PARAMICS, AIMSUN, MOTUS). Notice that few studies realistically consider AV lane changing behaviors.

Based on the theoretical findings summarized above, one can conclude that AVs are likely to improve system performance when penetration rates reach at least 20-30%. However, it is important to note that these estimates are solely based on computer simulations due to the lack of data collected from on-road automated vehicles. Therefore, such benefits are only estimates. For penetration rates below this threshold, there seems to be an agreement that negative effects to highway capacity will be small and will not require significant investment into capacity expansion [15]. At the same time, there is still significant uncertainty surrounding how AVs will interact with other AVs/human drivers, human driver response to AVs, technology capabilities by level of automation and manufacturer, technology development timelines, and feature settings (risk-taking versus risk averse, which can be influenced both by the manufacturer and user) that can significantly alter the theoretical benefits outlined above. For these reasons, it is important to study and incorporate these known areas of uncertainty into simulation tasks to extract the full range of potential scenarios for improved decision making.

In theory, AVs can lead to significant improvements to highway capacity primarily due to quicker reactions (e.g., faster computation, real-time controls) and improved decisions (e.g., more data) leading to smaller (safe) time headways. However, these findings are based on simplified assumptions that are not in alignment with real-world observations. This gap between theory and practice is often present in the academic literature because research typically focuses on idealized, future conditions. However, since the primary goal of this analysis is to generate topics to inform practical decisions in the near- to mid-term, it is important to identify these discrepancies and account for them in modeling and planning exercises.

The first simplified assumption that most studies make is that all AVs behave homogeneously. While it is likely that overall vehicle-level heterogeneity will decrease during the AV transition, the homogeneous assumption is too strong for several reasons. First, different AV systems and features have different capabilities and settings. For example, Mohammed & Horvath [36] found that time gaps and risk-taking behaviors varied between manufacturers and sensor types for ACC systems. The VW radar-based system was more conservative from a time gap perspective compared to the Volvo camera-radar combined system (both were set to minimum gap lengths). The Adaptive Cruise Control standard (ISO 15622) requires auto manufactures to provide minimum time gap settings greater than 0.8s (even as some theoretical studies use 0.6s) with a default setting between 1.5-2.2s. This range of car-following settings for commercial ACC spans the critical time headway found in the literature (1.2-1.5s), which means that capacity gains/losses could be dependent on how many drivers opt out of the default setting. From a modeling perspective, it is important to consider this full range of potential headway settings to generate realistic results in the near term. Additionally, there is human behavioral issue to consider as people tend to accept the default condition [37].

Next, theoretical studies assume time headways that are not realistic, at least with the technology available today or in the near-term. Based on a real-world study that collected data from eight participants for at least four months found that average headways for ACC users increased by 17%, 26%, and 40% in free flow, capacity, and congested conditions, respectively [38]. Several other studies have corroborated this increase in average time headways when

ACC is activated through real-world data collection [15, 39]. More specifically, Calvert, et al. [15] found that real-world desired time gaps for ACC were 1.2-1.8s compared to 0.5-1.5s for human drivers. These findings are a combined result of user selected settings, manufacturer settings, and current technology capabilities. It is also important to consider how manufacturer settings will change when vehicles transition from lower (SAE L1-L2) to higher (SAE L3-L5) levels of automation. This transition shifts liability from the driver to the manufacturer, which could impact default settings, likely in the conservative direction.

Third, significant uncertainty exists surrounding how humans respond to and interact with AVs. Up until this point, most research has focused on how AV technologies can reduce headways and smooth traffic based on instantaneous control. However, human interactions and vehicle behaviors adjacent to AVs will be different compared to their interactions with other human drivers. For example, using an open dataset provided by Waymo[4], Hu, et al. [40] found that human drivers were more aggressive when following a Waymo vehicle. Similar behaviors were observed in European field tests, where human drivers adopted smaller gaps around AVs and maintained smaller headways after overtaking an AV [41]. Therefore, it is important to capture and model these new types of behaviors, which depend on who is operating the vehicle (software/human), in mixed traffic environments.

Finally, the traffic flow impacts of AV lane changing behaviors in mixed traffic environments without connectivity are simply not considered in most AV highway capacity studies [1, 12]. Therefore, highway capacity improvements observed in many simulation studies may not be realistic in the near- to mid-term because AV lane changes are not directly modeled. Previous studies using real-world AV data have found that average time headways increased due to larger acceptance gaps. At the same time, speed and yaw volatility of following vehicles decreased, thereby reducing system heterogeneity and oscillations. How these impacts interact across different locations, conditions, and contexts are not yet well understood.

In addition to time gaps and lane changing behaviors, overall system stability is also an important consideration because instability reduces capacity. In the highway context, a system is not stable when reactions to disturbances (e.g., hard accelerations/decelerations) are amplified, leading to stop-and-go waves. When determining how AVs contribute to traffic (in)stability, one must consider both the causes of instability and the responses to perturbations. From a cause perspective, AVs can reduce system heterogeneity due to smoother controls compared to human drivers, which leads to more constant speeds, smoother accelerations/decelerations, and decreased variations in speed [1, 38]. Based on these

[4] https://waymo.com/

assumptions, the overall number of disruptions/perturbations can be reduced as AV market penetration rates increase. In mixed traffic environments, the responses to these perturbations will also be important, which is referred to as string stability. A system is considered string stable if responses to perturbations dampen (as opposed to amplify) over time. In general, longer headways and shorter reaction times lead to improved stability due to smoother responses. In a study by Talebpour & Mahmassani [28], AVs prevented wave formation and shock penetration, and improved string stability at 90% AV penetration. Liang & Peng [42] found that interspersed ACC vehicles with human-driven vehicles can lead to string stability. Other studies have corroborated these findings using theories about how ACC should behave [43, 44]. Overall, the general finding from theoretical/simulation-based literature is that AVs are likely to lead to more stable conditions that improve at higher penetrations. AVs can both reduce the number of disruptions (smaller variations in speeds leading to smoother driving) and contribute to smoother responses that dampen subsequent reactions rather than amplifying them [35].

The challenge with accepting these theoretical results for near-term operational planning is that real-world studies have found that commercial ACC features are string unstable [45, 46]. In Shang & Stern [46], ACC models that were calibrated with commercially tested ACC data were compared with theoretical models that made strong assumptions about AV reaction times and time headways. Theoretical modeling showed increased throughput by 7% at 100% AV penetration rate and string stability. ACC models that were calibrated using real-world data resulted in a 35% decrease in capacity and were found to be sting unstable, contradicting theoretical findings. Makridis, et al. [45] tested five different vehicles with ACC and found that controller reaction times were between 1.7-2.5s, which are significantly higher than the values often used in the literature. Interestingly, the electric powertrain had the lowest reaction times amongst the vehicles tested. In both cases, commercial ACC vehicles were found to be string unstable. Additional discrepancies were documented in other studies related to impacts at various penetration rates of ACC vehicles when considering commercial technologies. For example, Calvert, et al. [15] calibrated microsimulation models based on real-world ACC data collected by Gorter [38]. The Intelligent Driver Model plus (IDM+) was used for longitudinal control and the Lane-change Model with Relaxation (LMRS) was used to model lane changing behaviors. A three-lane freeway corridor was modeled with a nominal speed limit of 100km/hr. The study found that penetration rates would have to reach 70% before traffic throughput improvements were observed, which is much higher than the critical penetration rates derived from theoretical studies (20-40%) not calibrated with real-world data. James, et al. [47] calibrated four different car-following models with commercial ACC data collected from a 2013 Cadillac SRX. Simulation studies found that commercially calibrated ACC vehicles improved traffic flows at penetration rates below 25% but degraded capacity when penetration rates exceeded 75%. This result contradicts previous findings, indicating that further research is needed to better quantify the impacts of commercial ACC on traffic flow. The general takeaway from these studies is that theoretical studies are overly optimistic when it comes to predicting capacity improvements and string stability for AVs in real-world settings. One approach to mitigate this issue is to calibrate models with commercial data rather than making simple assumptions as to how AVs could behave at a future time.

2.4 Role of Human Factors

Human abilities, choices, behaviors, and interactions with automated vehicle features will largely determine the magnitude and direction (positive or negative) of capacity impacts. Theoretical studies highlight potential benefits based on current and future technology capabilities. However, many real-world studies have contradicted these findings, in part due to human choices and behaviors. In fact, Viti, et al. [48] argues that capacities will be mainly determined by human factors even at the higher levels of market penetration. This is because most drivers use ACC for comfort, not for efficiency. This leads to setting selections that prioritize comfort over efficiency. Additionally, significant uncertainty exists at the vehicle level related to human-AV interactions and responses. Calvert, et al. [15] and Yu, et al. [12] highlight these shortcomings in current microsimulation frameworks and recommend further research to inform the development of more advanced models that include these new interactions. This review focuses on a few key areas directly related to capacity and stability, and are as follows:

- Human choices and behaviors for low levels of automation (L1-L2)
- Human overtaking (L1-L3)
- Human response to automated driving features (L1-L4)

Various research studies have shown that the use of ACC (L1-L2) alters driving behaviors in different ways. Strand et al [49] and van Twuijver & Pol [50] found that ACC led to fewer lane changes and more time spent in the right lane. Viti et al. [48] found that drivers preferred stable speeds over stable headways and prioritized comfort over efficiency when selecting ACC settings. Alkim, et al. [51] found that drivers shift lanes earlier to overtake when ACC was engaged to prevent the ACC system from braking. Gorter [38] found that ACC users didn't manually reduce factory headway settings even when the drivers agreed that they were too large. In summary, even low levels of automation are changing driving behaviors, and most are prioritizing safety and comfort over efficiency. Therefore, in the near-term as L1-L2 ACC gains market share, it will be important to consider these behaviors in modeling tasks by adjusting parameters that add additional weight to safety and comfort.

The traffic impacts of human takeover processes have seen limited attention in the literature due to the uncertainty associated with the takeover process. However, most of the automated vehicle features available today do require human supervision and takeover when certain conditions arise. The consensus related to takeovers is that it will take longer for drivers to takeover tasks and gain full awareness when coming from a distracted state. To support this hypothesis, Kuehn, et al. [52] used a driver simulator study to conclude that it took distracted drivers (hands-free and multi-tasking while automated features were engaged) 12-15 seconds to fully takeover a vehicle and gain awareness of the driving situation compared to 8-10 seconds for manual drivers solely responsible for all driving tasks in similar situations. Numerous research studies have confirmed that level of focus decreased, and response times increased when using ACC [see Table 6 in Gorter [38]]. As of now, it is unclear how these processes will impact headways and traffic stability, but based on the observed changes in behavior, further research is warranted to better understand how these processes impact speeds, accelerations, and headways. The traffic impacts of various failover protocols (the process the vehicle goes through when a human can't take full control in a reasonable amount of time) is another important area for future research as no studies were identified as part of this literature review.

Finally, driver behaviors in response to AVs operating on the same roadways are not well understood yet can have significant impacts on capacity and stability. As mentioned earlier, some early examples of human drivers behaving more aggressively around AVs have been observed in multiple studies [40, 41]. These findings indicate that human drivers might try to exploit AV technology to improve their own situations.

In summary, a deeper understanding of human interactions, choices, and behaviors surrounding automated vehicles will be important to integrate such behaviors during AV modeling tasks. Early research has shown that human behaviors and choices will directly impact traffic capacities and stability. The prioritization of comfort (fewer driving tasks, constant speeds) for ACC is anticipated to result in longer headways and decreased capacities. Additionally, industry typically abides by ACC standards (e.g., ISO 15622), which requires default time headways to be between 1.5-2.2s, which are longer than observed time headways for human drivers. Other studies have documented long takeover times, which may or may not directly impact average time headways or lane changing behaviors (more research needed). However, these longer takeover events will likely impact traffic safety (incidents), which has been shown to contribute to 25% of total delays in the Netherlands and UK [15]. Finally, early research has found that human drivers will likely take advantage of AVs in many situations if AVs can be identified based on external hardware or other signals that indicate the vehicle is operating in autonomous mode. However, more data and research are needed to corroborate these initial findings. To conclude, shifting human driving behaviors resulting from L1-L2 automation (ACC), overtaking behaviors and how they can impact following distance, speed, and accelerations, and human response to other AVs on the roadways are all important topics that warrant further study to enhance modeling approaches for near-term applications.

2.5 Identified Research Gaps and Challenges

Numerous research and modeling gaps and challenges were identified as part of the literature review, and are as follows:

- Gap in findings between theoretical simulation studies and real-world observations. Theoretical studies are overly optimistic in their assumptions about car-following behaviors, which is at odds with data collected from commercially available ACC systems. These differences in assumed and observed time headways, following distances, and reaction times result in contradictory findings related to AV impacts on highway capacity [12, 15].
- Limited research that integrates realistic AV lane changing behaviors into microsimulation models for highway capacity planning [1, 12]. Most existing studies assume connectivity (or cooperative lane changing), which is not realistic in the near- to mid-term. Other studies

have focused on optimized controls, which, while important, does not capture realistic lane changing behaviors in mixed traffic environments.

- Lack of empirical data that captures lateral behaviors for different levels of automation. As new technologies are introduced that allow for automatic lane changes at lower levels of automation, new data will need to be collected to capture these lane changing behaviors for realistic modeling exercises.
- Limited understanding related to human-AV interaction behaviors, how human behaviors vary with different levels of automation, and how different technology capabilities, settings, vehicle types, and risk behaviors will impact AV car-following and lane changing [12].
- There is a need to update traffic modeling approaches to either couple AI techniques with existing methods or develop new methods based on AI when data becomes available to accurately capture behaviors from AI-based algorithms used in AVs [12].
- Limited research addressing the role of infrastructure management in mixed traffic situations [12].
- Limited understanding of manufacturer approach to designing automated features. This includes how manufacturer settings might be different between lower (SAE L0-L2) and higher (SAE L3-L5) levels of automation when liability shifts from the driver to the manufacturer [35]. This also includes risk appetites.
- Lack of knowledge related to AVs' effects on safety (e.g., quicker reaction times, driver distraction, awareness), and how these ultimately impact capacities and throughput at the macroscopic level [15].
- General lack of understanding related to the capabilities of different sensor types and automated features across manufacturers [36].
- Large uncertainty surrounding AV lane changing behaviors. Do AVs require more space based on manufacturer settings? Or less space based on enhanced vision? And how will they execute the lane change. Current methods to integrate AVs based on human lane-changing models will overestimate traffic capacities in simulations [15, 34, 35].
- Limited studies integrating optimized trajectory lane changing models into more traditional microsimulation frameworks to explore capacity impacts of automated lane changes.
- Limited studies evaluating capacity and stability impacts resulting from imperfect automation, different vehicle types (including medium and heavy duty), and in realistic road environments (e.g., complex configurations, roadway gradients), which are all components that must be considered for real-world operational planning [35].
- No differentiation between lower- (SAE L1-L2, e.g., ACC) and higher-level (SAE L4 with more robust hardware and improved computation) controls. Most research uses ACC controls [35].
- More empirical data is needed to study vehicle dynamics and intervehicle interactions as automated features become more widespread [26].

3 Timeline of Impacts

In 2020, more than 80% of new vehicles worldwide had L1/L2 features, which is expected to grow to nearly 95% in 2025 [53]. In addition, new more advanced automated features—referred to as L2+/L2.5 and L3—are coming to market offering new capabilities (hands-free driving with adaptive cruise control, automatic lane changing, and lane keeping assist) that can significantly impact demand for new automated driving features. One difference between L2/L2+ and L3 comes down to driver responsibility. L2/L2+ features require constant driver supervision while L3 features allow the driver to disengage from driving tasks when specific conditions are met. It is important to note that automation levels and/or feature names provided by manufacturers are not consistent nor do they clearly describe the vehicle's automation capabilities. In addition, the automation level alone is not a good indicator of technology maturity. For example, the two L3 systems mentioned below do not perform lane changes, while many L2+ systems perform hands-free driving with automatic lane changing. Some commercial examples of such systems are as follows:

- General Motors Super Cruise is an L2+ hands-free feature that includes ACC and automatic lane changing (the vehicle determines when lane changes are necessary based on vehicle speeds in current and target lanes and executes the lane changes without human intervention) on a network of pre-mapped roadways totaling over 750,000 miles [54].
- Ford BlueCruise is an L2+ hands-free feature that includes ACC, lane change assistance (hands-free lane changes when a lane change is requested by the driver), and in-lane repositioning on a network of pre-mapped roadways totaling over 130,000 miles.
- Nissan Pro-PILOT 2.0 is an L2+ hands-free (when operating in a single lane) feature that includes ACC, route assist, and lane change assist (lane change will happen after the driver places their hands on the steering wheel, activates the turn signal, and the vehicle sensors determine that the lane change is safe to execute) between on-ramps and off-ramps on a pre-mapped network totaling over 200,000 miles [Pro-PILOT Compatible Roads].
- BMW Highway Assistant is an L2+ hands-free feature driving at speeds up to 85mph and includes Active Lane Change (hands-free lane changes [confirmed when driver glances at a side mirror] at speeds above 40mph when the vehicle approaches slower moving vehicles in the lane ahead), ACC, and Lane Keeping Assistant.
- Tesla Full Self Driving is an L2+ system with ACC, automatic lane changing, and lane keeping assist (referred to as Autosteer). Full Self Driving is not limited to freeways, can start/stop at traffic lights and stop signs, and requires continuous driver supervision.
- Mercedes-Benz Drive Pilot is an L3 feature that allows the driver to take their eyes off the road when certain conditions are met (speeds less than 40mph, presence of a leading vehicle, clear lane markings, moderate/heavy traffic, no construction zones present, clear weather, daylight hours, and must be used on pre-mapped roads). Drive Pilot does not change lanes. The system must be deactivated to execute lane changes.

- BMW Personal Pilot L3 has similar functionality as Mercedes-Benz's Drive Pilot, yet it can be used in the dark. System testing started in Germany in March 2024 with a goal to be introduced in the U.S. in the coming years. Personal Pilot does not perform lane changes; however, Personal Pilot can be combined with Highway Assistant, which includes active lane changes when certain conditions are met.

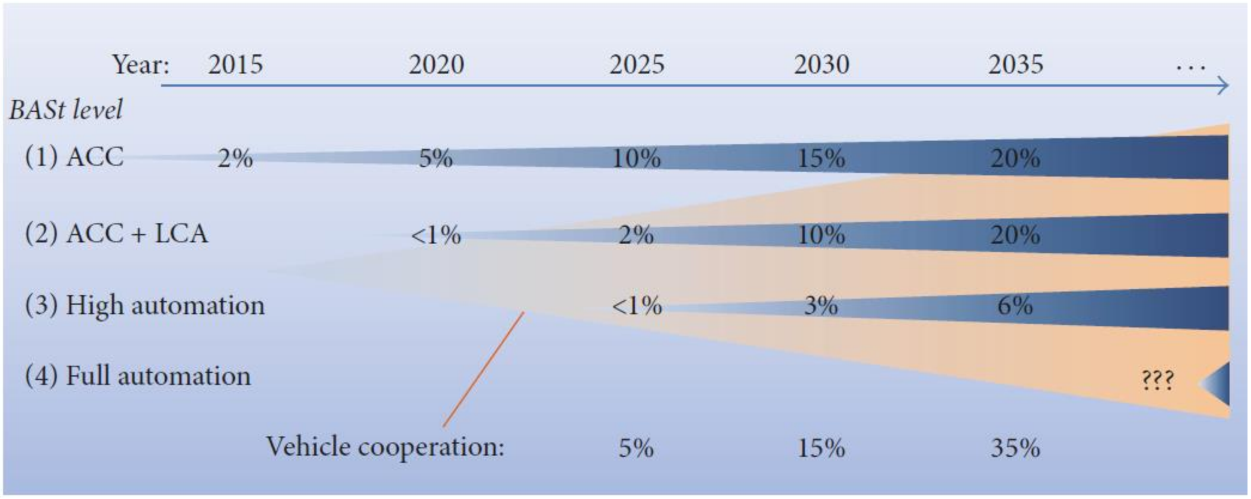
Currently, commercial L4 systems are not available for private purchase. However, L4 technologies continue to be developed and deployed in commercial settings, such as for ride-hailing and long-haul/middle-mile freight applications. As fleets continue to grow, it is anticipated that these L4 technologies will increasingly contribute to freeway efficiency; however, it is still unclear whether the impacts will be positive or negative due to lack of transparency related to how the L4 vehicles make decisions.

The emergence of numerous automation offerings from different original equipment manufacturers (OEM) and service providers will impact freeway efficiencies in diverse ways. The ability to quantify and model these impacts will be difficult from the technology perspective because settings and performance will vary across manufactures based on their technology maturity and risk appetite. However, a combination of real-world testing, human factors analysis, and theoretical modeling can help reduce these uncertainties to help inform operational decisions to best prepare for AV integration. The purpose of the following section is to estimate technology development, deployment, and human acceptance over the near- to mid-term to best predict potential scenarios for AVs operating on U.S. roadways. It is also important to remember that the average age of light-duty vehicles in the U.S. is between 10-15 years [55, 56], which means that it will take time for the existing fleet to turnover once new technologies are introduced into new vehicles. One study found that it takes close to 20 years to reach 90% penetration for a new vehicle technology, even if 100% of new vehicles were equipped during the first year [57].

3.1 Technology Development

Automated vehicle technologies continue to progress, albeit at a slower pace than many researchers and industry professionals previously thought. In 2021, a survey of 75 industry professionals predicted that L4 features would be available in private vehicles for highway driving by 2024. Additionally, the study predicted wide-spread availability of automated on-demand services in operation by 2028 and driverless full journeys by 2031 [58]. A follow-up to this survey conducted in 2023 of the same population saw projections pushed back and timelines extended (L4 highway availability in 2027, automated on-demand services in 2029) [59]. This trend of extending timelines has been regularly observed over the last decade due to various technology and policy challenges for automated vehicle features.

As of 2021, 92% of new cars had ACC (L1) and 50% of new cars had L2 capabilities, meaning that both steering and speeds could be controlled by the vehicle [60]. However, the market penetration rate of L1-L4 features is still well below 25% due to the long fleet turnover period [15]. In addition, this only represents the number vehicles equipped to use ACC, which is likely much higher than the number of vehicles that will regularly use ACC. Calvert et. al [15] estimated penetration rates for different levels of automation using estimates from nine different sources from academia, industry, and government (see **Figure 2** below).



Source: Calvert, Schakel, and van Lint (2017)

Figure 2 - Projected Penetration Rates for Different Automated Vehicle Features in Five Year Increments [2015-2035] Including ACC, ACC+LCA, High Automation, and Full Automation

Other studies have projected a transition of several decades with significant penetration (>50%) of L3/L4 vehicles not occurring until closer to 2045 [61]. A recent report by Souweidane & Smith [62] estimated that only 55% and 5% of new vehicle sales will have L2 and L3 features, respectively, by 2030. Litman [63] predicts that the majority of U.S. fleet vehicles will not be able to operate at high levels of automation until the 2040s or 2050s. Note that these estimates are different than the number of new vehicles that have the option to add L2/L3 features.

To summarize, significant uncertainty exists related to fleet share of automated vehicles (L1-L5) in the near- to mid-term. Based on projections related to new vehicle sales and fleet turnover timelines, the highest possible market penetration rate for L1/L2-equipped vehicles will likely be 20-30% by 2030. Vehicles with higher levels of automation are not expected to make up a significant portion of the vehicle fleet by 2030. This proportion (20-30%) is similar to the critical penetration rate to first start seeing efficiency benefits outlined in the theoretical literature. However, this critical threshold is contingent on several overarching assumptions, including that ACC time gaps are lower than human time gaps, which hasn’t been observed with commercial ACC. The penetration rate also only accounts for the number of vehicles equipped with these technologies, and not the adoption rate.

3.2 Connectivity

Vehicle-to-everything (V2X) technologies promise widespread benefits to safety and efficiency. When paired with vehicle automation, real-time data can be shared between vehicles and infrastructure, which provides an additional layer of information outside sensor line of sight to complement automation features. For example, V2V communications allows upstream vehicles to alter their speeds proactively during a downstream disruption, rather than waiting for onboard sensors to perceive and react to changing speeds from their leading vehicle. Additionally, V2X enables cooperative merges and/or lane changes, which allows for vehicles to communicate speeds and intentions to adjacent vehicles and adjust their speeds to create gaps for smooth merging. However, the initial penetration rates of cooperative driving automation technologies are low and are not considered in most near-term studies.

In recent years, C-V2X has become the leading technology to provide vehicle-to-everything (V2X) communications due to the Federal Communications Commission's (FCC) reallocation of 30MHz of the previously dedicated DSRC spectrum in 2022. C-V2X provides low-latency, safety critical direct communications, which are needed for many cooperative driving applications. Currently, the development and deployment of V2X technologies has been mostly limited to infrastructure owner-operators (IOO) as auto manufacturers and suppliers wait for a final ruling from the FCC related to ITS [64]. It is expected that it will then take 3-5 years for auto manufacturers to integrate onboard V2X technologies with their current automated driving electronics.

From a technology standpoint, much of the V2X hardware has already been developed to transmit basic messages to vehicles and infrastructure. The challenge with connected transportation systems is that significant market penetration is needed to provide sufficient benefits (individual and system-level) across a broad range of stakeholders (e.g., IOOs, auto manufacturers, users). From a basic connectivity perspective, McKinsey estimates that 95% of new vehicles will be connected by 2030 (up from 50% in 2019) [65]. Therefore, one could expect that it will take another 10 years (due to fleet turnover) to reach sufficient penetration rates to observe widespread benefits from cooperative driving automation.

V2X connectivity also enables new traffic management strategies that can help mitigate negative outcomes and amplify benefits of the automated vehicle transition. In the highway context, these types of strategies are mostly related to managed/dynamic lanes and cooperative merging. Several studies have analyzed different strategies for managed lanes in mixed traffic environments under different assumptions, conditions, and use cases. Amirgholy, et al., [66] found that corridor throughput can improve significantly with dedicated AV/CAV lanes when the market penetration rate is high. At low penetration rates, corridor delays increased with dedicated lanes. A different study found that mixed lanes (allowing both human drivers and AVs) were optimal when market penetration rates were below 50% or greater than 65% [67]. Similar findings were observed in Zhong, et al., [68], in that dedicated CAV/AV lanes improved throughput when market penetration rates were approximately between 40-70%. Khattak, et al.,

[69] analyzed cooperative merging strategies during unanticipated lane closures. The study found that throughput increased, and volatility decreased with increasing percentage of CAVs. In conclusion, connectivity can help manage the AV transition in different ways. However, benefits to freeway capacity and throughput due to managed lanes and cooperative merging strategies will not be realized until penetration rates are on the order of 40-70% (over 10 years away based on current projections).

In summary, widespread highway capacity benefits of cooperative driving automation, cooperative adaptive cruise control (CACC), and V2X connectivity are likely decades away. Therefore, near-term AV modeling efforts should not consider connectivity when analyzing freeway throughput. However, in longer-term capacity planning exercises, connectivity can help negate negative impacts of high ACC penetration rates (e.g., instability) by adding a new layer of real-time information for improved decision making.

4 Gaps, Challenges, and Next Steps

Based on the literature reviewed and projected timelines for technology development and deployment, it is expected that most near-term traffic impacts will be due to lower levels of automation. Therefore, new modeling approaches are needed to capture L2+ and L3 capabilities, their realistic behaviors (e.g., reaction times, OEM risk tolerance, human gap settings), and how human drivers use and interact with these features inside the vehicle and respond to other AVs in mixed traffic environments.

More broadly looking at research needs over the next 10 years, the identified gaps/challenges loosely fall into three overarching topics/themes: 1) Simplified, unrealistic modeling assumptions, partially explained by lack of empirical data, 2) Limited understanding related to human-machine interactions and cooperation, and 3) New modeling frameworks needed to capture realistic AV behaviors. The following sections will summarize research gaps related to the three overarching themes to help motivate future research and deployment activities.

4.1 Summary of Gaps/Challenges

Simplified, unrealistic modeling assumptions:

- Theoretical simulation studies assume perfect technology performance and limited impacts from human factors. These assumptions are overly optimistic and inaccurate in the near- to mid-term, which can impact capacity planning. For example, numerous studies found that commercially available ACC systems degraded performance due to longer reaction times, longer desired time headways, and greater instability, which contradicts findings from the simulation-based literature.
- AV (L2-L4) lane changing behaviors (and resulting behaviors from adjacent human driven vehicles) are rarely considered in highway capacity simulation studies in mixed traffic environments without connectivity. This is partially due to the lack of understanding due to limited empirical data.
- Most literature assumed homogeneous behavior for AVs. However, automated features have different capabilities (based on hardware/software stacks and levels of automation), controls, and risk attitudes (as programmed by the developer) that vary between OEMs.
- There is a lack of studies that consider realistic environments (weather, road gradients, complex configurations), imperfect automation, and different vehicle types including medium and heavy vehicles (which will rely on different hardware and control algorithms). The performance of AV features and human responses across a diversity of conditions will ultimately determine the costs and benefits of AVs operating in the real-world.

Limited understanding related to human-machine interactions and cooperation:

- Lack of research related to how human-machine interactions and cooperation within the vehicle for L1-L3 features will impact car following and lane changing behaviors, such as takeover events, transfer of control, and failover procedures.
- Initial studies found that human drivers will take advantage of AVs in certain conditions, which can impact safety and efficiency. Further research is needed to identify how human driving behaviors might change in the presence of AVs.

New modeling frameworks needed to capture realistic AV behaviors:

- Traditional car-following and lane-changing approaches that model human behaviors are also being used to model AVs by modifying inputs related to reaction times and headways. This approach, while intuitive, is limited in its ability to capture AV behaviors due to its inability to model the underlying data-driving decision-making process that includes sensor inputs, data fusion, recognition, machine learning/AI, and optimized decision making.
- Assumptions about vehicle controllers are idealistic and do not consider different levels of automation with different hardware/software capabilities (standard ACC algorithms primarily used in research). Controls will also vary based on conditions and vehicle types, which is an area with limited research.
- Limited understanding related to AV lane changing behaviors (e.g., trajectories, risk attitudes, execution), which are based on sensor inputs and data-driven decision making.
- Lack of studies assessing highway capacity improvements due to increased safety provided by AVs (e.g., smoother trajectories, reduced speed variance).

4.2 Recommendations for Future Research

Most theoretical simulation studies assume ideal conditions, simplified environments, high levels of technology performance, simplified lateral behaviors, and homogeneous capabilities for all AVs within the traffic stream. These assumptions are overly optimistic for near-term modeling and operational planning. Therefore, there is a need to study how AV technologies and driver preferences (e.g., time headways, lead/lag gaps for lane changes, probability of lane changes under different conditions) impact driving behaviors across a wide range of real-world environments. Examples of such environments include weather (e.g., ice, wind), daylight (e.g., low-lighting, dark), and roadway geometry (e.g., winding roads with significant gradients). Additionally, AV lane changing behaviors and human driver responses to AVs in mixed-traffic environments is also critical for realistic capacity assessment. This consideration becomes more important as many manufacturers are now deploying various forms of automated lane changing technologies that differ in capabilities and human driver responsibility. To date, few studies have analyzed AV-specific lane changing behaviors that include adjacent vehicle responses.

The popularity of hands-free automated features has grown in recent years due to more advanced automated controls capable of easing driving tasks. The difference between L2+ and L3 hands-free systems is that L2+ requires constant human supervision while L3 allows for the driver to engage with other tasks in certain ODDs. In both cases, more complex human-machine interactions are required to switch control, which can result in disruptions. Additionally, failover protocols for commercially available L3 systems require the vehicle to slowdown in their lane until the vehicle is stopped and call emergency services when human drivers fail to takeover driving tasks in a reasonable amount of time. While this failover strategy appears to be safe for the in-vehicle driver and surrounding vehicles, it is unclear how this sequence of actions will impact highway capacity. Additionally, it is unclear how technology capabilities and ODDs will impact the frequency of failover events. Therefore, there is a need to study human-machine interactions and failover protocols, specifically for hands-free systems available today (L2+/L3), and to incorporate these behaviors in modeling and simulation activities.

AV and human decision-making processes are fundamentally different, which calls for new methods and frameworks to model and simulate these two sets of behaviors simultaneously. The most widespread approach to modeling AVs (to date) is to modify input parameters using previously developed human behavior models. However, this approach does not capture the underlying AV decision-making process, which can limit future modeling enhancements and applications. Therefore, there is a need to develop and incorporate AI-based decision-making processes into current traffic modeling and simulation tools.

Finally, average roadway capacity can be significantly impacted by incidents and collisions, which is another area that AVs can positively contribute in terms of mitigation/prevention. To date, few studies have explored capacity impacts resulting from changes in safety performance for AVs, which is an area that needs further research to accurately assess AV impacts to highway capacity.

5 References

[1] N. Raju and H. Farah, "Evolution of Traffic Microsimulation and Its Use for Modeling Connected and Automated Vehicles," *Journal of Advanced Transportation,* 2021.

[2] X. Wen, C. Huang, S. Jian and D. He, "Analysis of discretionary lane-changing behaviors of autonomous vehicles based on real-world data," *Transportmetrica A: Transportation Science,* 2023.

[3] Y. Ali, A. Sharma and D. Chen, "Investigating autonomous vehicle discretionary lane-changing execution behaviour: Similarities, differences, and insights from Waymo dataset," *Analytic Methods in Accident Research,* vol. 42, 2024.

[4] American Automobile Association (AAA), "Advanced Driver Assistance Technology Names," 2019.

[5] V. Milanes and S. Shladover, "Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data," *Transportation Research Part C,* vol. 48, pp. 285-300, 2014.

[6] B. Schroeder, A. Morgan, P. Ryus, B. Cesme, A. Bibeka, L. Rodegerdts and J. Ma, "Capacity Adjustment Factors for Connected and Automated Vehicles in the Highway Capacity Manual," 2022.

[7] H. Ahmen, Y. Huang and P. Lu, "A Review of Car-Following Models and Modeling Tools for Human and Autonomous-Ready Driving Behaviors in Micro-Simulation," *Smart Cities,* pp. 314-335, 2021.

[8] T. Zhang, P. Jin, S. McQuade, A. Bayen and B. Piccoli, "Car-Following Models: A Multidisciplinary Review," 2024.

[9] R. Wiedemann, "Simulation des Strassenverkehrsflusses," University Karlsruhe, 1974.

[10] PTV, VISSIM 5.40 User Manual, 2012.

[11] R. Wiedemann and U. Reiter, "Microscopic Traffic Simulation: The Simulation System MISSION, Background and Actual State," 1992.

[12] H. Yu, R. Jiang, Z. He, Z. Zheng, L. Li and R. C. X. Liu, "Automated vehicle-involved traffic flow studies: A survey of assumptions, models, speculations, and perspectives," *Transportation Research Part C,* 2021.

[13] P. Gipps, "A model for the structure of lane-changing decisions," *Transportation Research Part B,* pp. 403-414, 1986.

[14] M. Ben-Akiva, C. Choudhury and T. Toledo, "Lane changing models," 2006.

[15] S. Calvert, W. Schakel and J. van Lint, "Will Automated Vehicles Negatively Impact Traffic Flow," *Journal of Advanced Transportation,* 2017.

[16] C. Daganzo, "The cell transmission model: A dynamic representation of highway traffic consistent with hydrodynamic theory," *Transportation Research Part B,* pp. 269-287, 1994.

[17] A. Aw and M. Rascle, "Resurrection of "second order" models of traffic flow," *Journal of Applied Mathematics,* pp. 1916-1938, 2000.

[18] H. Zhang, "A non-equilibrium traffic model devoid of gas-like behavior," *Transportation Research Part B,* pp. 275-290, 2002.

[19] R. Jiang, Q. Wu and Z. Zhu, "Full velocity difference model for a car-following theory," *Physics Review E,* 2001.

[20] N. Taylor, "The CONTRAM Dynamic Traffic Assignment Model," *Networks and Spatial Economics,* pp. 297-322, 2003.

[21] M. Ben-Akiva, M. Bierlaire, H. Koutsopoulos and R. Mishalani, "DynaMIT: a simulation-based system for traffic prediction," 1998.

[22] R. Jayakrishnan, M. Cohen, J. Kim, H. Mahmassani and T. Hu, "A Simulation-based framework for the analysis of traffic networks operating with real-time information," California Partners for Advanced Transit and Highways, 1993.

[23] K. Nagel and M. Schreckenberg, "A cellular automaton model for freeway traffic," *Physics Abstracts,* pp. 2221-2229, 1992.

[24] A. Horni, K. Nagel and K. Axhausen, "The Multi-Agent Transport Simulation MATSim," 2024.

[25] M. Levin, "Modeling and Optimizing Network Infrastructure for Autonomous Vehicles," University of Texas at Austin, 2017.

[26] S. Calvert and B. van Arem, "A generic multi-level framework for microscopic traffic simulation with automated vehicles in mixed traffic," Transportation Research Part C, 2020.

[27] K. Heaslip, N. Goodall, B. Kim and M. Abi Add, "Assessment of Capacity Changed sue to Automated Vehicles on Interstate Corridors," Virginia Transportation Research Council, 2020.

[28] A. Talebpour and H. Mahmassani, "Influence of Connected and Autonomous Vehicles on Traffic Flow Stability and Throughput," *Transportation Research Part C,* pp. 143-163, 2016.

[29] A. P. Carrone, J. Rich, C. A. Vandet and K. An, "Autonomous vehicles in mixed motorway traffic: capacity utilization, impact and policy implications," *Transportation,* pp. 2907-2938, 2021.

[30] W. Fan and P. Liu, "Impact of Connected and Automated Vehicles on Freeway Capacity," University of North Carolina, Charlotte, 2019.

[31] D. Mohammed and B. Horvath, "Vehicle Automation Impact of Traffic Flow and Stability: A Review of Literature," Acta Polytechnica Hungarica, 2023.

[32] D. Li and P. Wagner, "Impacts of gradual automated vehicle penetration on motorway operation: a comprehensive evaluation," *European Transport Research Review,* 2019.

[33] J. Erdmann, "SUMO's Lane Changing Model," in *Modeling mobility with open data*, Springer International Publishing, 2015, pp. 105-123.

[34] M. Al-Turki, N. Ratrout, S. Rahman and I. Reza, "Impacts of Autonomous Vehicles on Traffic Flow Characteristics under Mixed Traffic Environment: Future Perspectives," *Sustainability,* 2021.

[35] E. Aittoniemi, "Evidence of impacts of automated vehicles on traffic flow efficiency and emissions: Systematic Review," *IET Intelligent Transport Systems,* 2021.

[36] D. Mohammed and B. Horvath, "Comparative Analysis of Following Distances in Different Adaptive Cruise Control Systems at Steady Speeds," *World Electric Vehicle Journal,* 2024.

[37] R. Thaler and C. Sustein, Nudge: Improving Decisions about Health, Wealth, and Hapiness, Penguin Books, 2009.

[38] M. Gorter, "Adaptive Cruise Control in Practice," Delft University of Technology, 2015.

[39] A. Eilbert, I. Berg and S. Smith, "Meta-Analysis of Adaptive Cruise Control Applications: Operational and Environmental Benefits," U.S. Department of Transportation, Washington DC, 2019.

[40] X. Hu, Z. Zheng, D. Chen and J. Sun, "Autonomous Vehicle's Impact on Traffic: Empirical Evidence from Waymo Open Dataset and Implications from Modelling," *IEEE Transactions on Intelligent Transportation Systems,* pp. 6711-6724, 2023.

[41] S. Soni, N. Reddy, A. Tsapi, B. van Arem and H. Farah, "Behavioral adaptations of human drivers interacting with automated vehicles," *Transportation Research Part F,* 2022.

[42] C.-Y. Liang and H. Peng, "String Stability Analysis of Adaptive Cruise Controlled Vehicles," University of Michigan, 2000.

[43] A. Bose and P. Ioannou, "Analysis of traffic flow with mixed manual and semiautomated vehicles," *IEEE Transactions on Intelligent Transportation Systems,* 2003.

[44] L. C. Davis, "Effect of adaptive cruise control systems on traffic flow," *Physical Review E,* 2004.

[45] M. Makridis, K. Mattas, B. Ciuffo, F. Re, A. Kriston, F. Minarini and G. Rognelund, "Empirical Study on the Properties of Adaptive Cruise Control Systems and Their Impact on Traffic Flow and String Stability," *Transportation Research Record,* 2020.

[46] M. Shang and R. Stern, "Impacts of commercially available adaptive cruise control vehicles on highway stability and throughput," *Transportation Research Part C,* 2021.

[47] R. James, C. Melson, J. Hu and J. Bared, "Characterizing the impact of production adaptive cruise control on traffic flow: An investigation," *Transportmetrica B: Transport Dynamics,* 2019.

[48] F. Viti, S. Hoogendoorn, T. Alkim and G. Bootsma, "Driving behavior adaptation under ACC: results from a large field operational test in the Netherlands," *IEEE Intelligent Vehicles Symposium,* 2008.

[49] N. Strand, J. Nilsson, C. Karlsson and L. Nilsson, "Exploring end-user experiences: self-perceived notions on the use of adaptive cruise control systems," *IET Intelligent Transport Systems,* 2011.

[50] M. van Twuijver and M. Pol, "Car Owners Experiences with In-Car Speed Controlling Systems in the Netherlends," Association for European Transport, 2004.

[51] T. Alkim, G. Bootsma and P. Looman, "The Assisted Driver - Systems that support driving," Audi, 2007.

[52] M. Kuehn, T. Vogelpohl and M. Vollrath, "Takeover Times in Highly Automated Driving (Level 3)," *25th International Technical Conference on the Enhanced Safety of Vehicles,* 2017.

[53] K. Buchholz, "Cars Increasingly Ready for Autonomous Driving," Statista, 6 September 2024. [Online]. Available: https://www.statista.com/chart/25754/newly-registered-cars-by-autonomous-driving-level/. [Accessed 10 October 2024].

[54] E. Walz, "GM nearly doubles Super Cruise road network miles," Automotive Dive, 23 February 2024. [Online]. Available: https://www.automotivedive.com/news/general-motors-expands-super-cruise-miles-highway-hands-free-driving/708150/. [Accessed 10 October 2024].

[55] U.S. Energy Information Administration, "U.S. households are holding on to their vehicles longer," 2018. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=36914. [Accessed 20 August 2024].

[56] N. Parekh, "Fuel for Thought: Auto Safety Systems - Calibration challenges and opportunities," 2023. [Online]. Available: https://www.spglobal.com/mobility/en/research-analysis/fuel-for-thought-auto-safety-systems-calibration-challenges-repair-modification.html. [Accessed 20 August 2023].

[57] D. Keith, S. Houston and S. Naumov, "Vehicle fleet turnover and the future of fuel economy," *Environmental Research Letters,* vol. 14, 2019.

[58] K. Heineke, R. Heuss, A. Kelkar and M. Kellner, "What's next for autonomous vehicles?," Mckinsey, 2021.

[59] McKinsey, "Autonomous vehicles moving forward: Perspectives from industry leaders," 2024.

[60] J. Bartlett, "How Much Automation Does Your Car Really Have?," 2021. [Online]. Available: https://www.consumerreports.org/cars/automotive-technology/how-much-automation-does-your-car-really-have-level-2-a3543419955/. [Accessed 20 August 2024].

[61] Netherlands Institute for Transport Policy, "Paths to a self-driving future," Ministry of Infrastructure and the Environment, 2017.

[62] N. Souweidane and B. Smith, "Sate of ADAS, Automation, and Connectivity," Center for Automotive Research, 2023.

[63] T. Litman, "Autonomous Vehicle Implementation Predictions," Victoria Transpor Policy Institute, 2023.

[64] K. Sheriff, H. Moelter, J. Jandura and E. Kuka, "FCC Approves C-V2X Technology for Connected Vehicles Ahead of Final ITS Rules," 2023. [Online]. Available: https://www.dwt.com/blogs/broadband-advisor/2023/05/fcc-connected-vehicles-c-v2x. [Accessed 20 August 2024].

[65] T. Neumann, "Five Automotive Connectivity Trends Fueling the Future," Jabil, 2019.

[66] M. Amirgholy, M. Shahabi and O. Gao, "Traffic Automation and Lane Management: Communicant, Autonomous, and Human-Driven Vehicles," *Transportation Research Part C,* 2020.

[67] R. Mohajerpoor and M. Ramezani, "Mixed flow of autonomous and human-driven vehicles: Analytical headway modeling and optimal lane management," *Transportation Research Part C,* 2019.

[68] Z. Zhong, J. Lee and L. Zhao, "Traffic Flow Characteristics and Lane Use Strategies for Connected and Automated Vehicles in Mixed Traffic Conditions," *Journal of Advanced Transportation,* 2021.

[69] Z. Khattak, B. Smith, M. Fontaine, J. Ma and A. Khattak, "Active lane management and control using connected and automated vehicles in a mixed traffic environment," *Transportation Research Part C,* 2022.

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