Impacts of AV and CAV Technologies

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Autonomous vehicles (AVs) and connected autonomous vehicles (CAVs) are expected to have a significant impact on highways. The capacity impact of AVs will change based on their penetration in the vehicle fleet. For medium-term planning horizons, AVs will reduce capacities, whereas for long-term planning horizons and the buildout, capacities will be positively impacted.

Keywords: autonomous vehicle ; mixed traffic ; planning capacities

1. Introduction

Autonomous vehicles (AV) and connected autonomous vehicles (CAVs) are poised to change the way households and individuals own, drive, and operate their vehicles and how the transportation system performs and responds to traffic. Their introduction will potentially improve traffic safety [1][2], and roadway operation and capacities [3][4][5]. AVs and CAVs have the potential to increase capacity in traffic streams by reducing vehicle headway, improving reaction times and sensitivity to changing traffic conditions, and promoting a more consistent and efficient flow of traffic. The hypothesis is that existing roadways may be better equipped to handle an increased proportion of AVs and CAVs compared to the exclusively traditional vehicles present today. Although there is an increasing amount of literature on autonomous vehicles, the relationship between penetration timelines and different mixes of AVs and CAVs has yet to be fully understood. Transportation planners must comprehend these impacts as they develop long-range transportation plans, which are commonly designed to forecast land use impacts on the transportation system for a period of up to 30 years into the future. These plans serve as a basis for making significant transportation system-wide investment decisions and require the development of models incorporating land use, transportation systems, and sociodemographic forecasts to predict their impact on travel demand and the transportation system. With the potential introduction of AVs and CAVs, planners are currently faced with the question of how these vehicles will impact roadways within the planning horizon (20–30 years from now) and how they should plan accordingly. As AVs and CAVs do not currently exist, this question is being addressed through simulation models that replicate their operations.

2. Impacts of AV and CAV and Technologies Transportation Systems for Transportation Planning Horizons

AVs and CAVs are vehicles capable of performing driving functions, from assisting drivers with automatic cruise control and lane centering to fully driving the vehicle without any human intervention from start to finish. The concept of AVs/CAVs has been defined in various ways in the literature, based on the capabilities of the vehicles. For instance, the National Highway Traffic Safety Administration (NHTSA, 2016) categorizes AVs into six levels, based on the level of human intervention required in vehicle operation. Meanwhile, the Institute of Transportation Engineers (ITE, 2021) defines CAVs as having vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-mobile/smart device (V2X) connectivity via 5G.

The Coexist project (Coexist1.4, 2018) classifies AVs into three categories: cautious, normal, and all-knowing, with the latter being equivalent to a level 5 CAV from the NHTSA definition. However, the technologies and algorithms used in each class differ. For instance, an AV-normal vehicle can measure the distance and speed of other vehicles, slow down when its sensors detect blind spots, and avoid collisions, but it drives cautiously and leaves larger gaps in a traffic stream compared to traditional vehicles. On the other hand, CAVs can leave smaller gaps in a traffic stream, potentially increasing roadway capacities, as they incorporate V2X communication and more aggressive driving behavior. The impact of AVs/CAVs on highway capacity will be influenced by their driving behavior, particularly in oversaturated traffic conditions, and the level of penetration of these vehicles in the traffic stream along with traditional vehicles.

The gaps that these vehicles will leave in a traffic stream compared to traditional vehicles will play an important role in their highway capacity and operational impact. The impact becomes more pronounced under oversaturated traffic conditions, where traditional vehicles leave relatively smaller gaps and traffic is at stop-and-go speeds. The driving algorithms of AV-cautious vehicles may result in larger gaps in front of them compared to traditional vehicles, potentially reducing highway capacity. Conversely, CAVs have the potential to leave smaller gaps and increase roadway capacity. This issue is further complicated by the presence of AVs/CAVs at varying penetration levels and coexisting with traditional vehicles in the same traffic stream.

The market penetration of AV/CAVS will perhaps have the most significant capacity impact up until they reach critical mass in the vehicle fleet and in the amount of travel that occurs by them. Current research shows that AVs are expected to take longer to be accepted than other vehicle technologies [6][7]. Several factors including safety [8], psychological [9], trust [10] and perceived usefulness/risk [11]. These studies show that these factors will play an important role in the adoption cycles for AVs. Thus, the study uses the current state-of-the-art in future forecasts for AVs. These forecasts could change and have changed over the past several years. However, this research is developed to aid planners with accounting for AVs in their transportation plans. These plans are updated every five years in the U.S. and it will be appropriate to revisit AV forecasts periodically and adjust models accordingly. Therefore, significant capacity impacts may probably be seen 20 to 30 years from now. Regarding AV/CAV vehicle penetration, it is estimated that 50% of new vehicle sales will be AVs by 2045, and half of the fleets will be autonomous by 2060 [12]. **Figure 1** shows the forecasts of AV and CAV market penetration, travel, and fleet size over the next 60 years for potential worst and best cases [12]. It shows that by 2050, which is the current long-range planning horizon year for metropolitan planning organizations in the U.S., travel by AVs/CAVs will be about 40% of total vehicle miles traveled. This is significant and will have different implications compared to the forecast year 2035 which is in the current mid-range planning horizon with about 15% penetration with mostly AV-cautious cars.

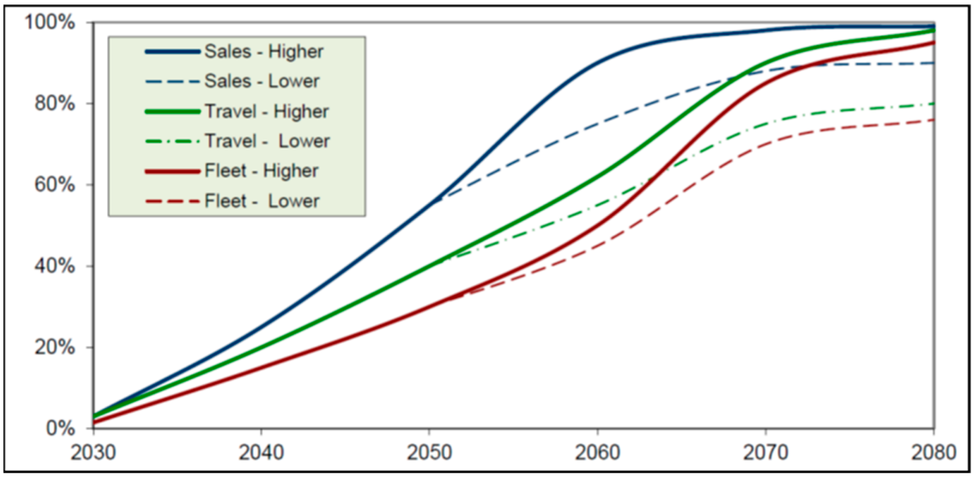

Figure 1. Autonomous Vehicle (AV) Sales, Fleet, and Travel Projections [12].

The effect is that transportation capacities will become fluid and change as AVs and CAVs change in the general vehicle population. For example, according to **Figure 1**, significant benefits of AV/CAVS may only be realized after the year 2050. Since the planning horizon for most long-range transportation plans is 30 years in the U.S., it is possible that the full benefits will not materialize within the current long-range transportation plan horizons. In contrast, there are potentially negative impacts on capacity with lower penetrations and less aggressive technology. It is thus essential to correctly quantify the capacity impacts of AVs and CAVs to make optimal transportation system decisions over different planning time horizons. These impacts need to be investigated so that planners can make optimal decisions about their transportation system investments. Several studies have estimated the capacity impacts due to AVs and CAVs, with most showing improvements in capacities based on penetration rates, traffic conditions, and roadway types. Three main frameworks are used in the literature to evaluate these impacts, including mathematical formulations, simulation methods using synthetic data, and using real-world data to simulate these impacts.

A theoretical-mathematical formula was used to investigate the influence of vehicular technology on the car-following model [13]. The results showed potential capacity improvements ranging from 20% to 50%. Another research found that AVs/CAVs decreased headway and at higher penetration levels increased capacity by up to 36% [14][15]. Mathematical models are good initial models that are incorporated into simulations that mimic real-world traffic behaviors and can be validated against real-world data.

Sensors and vehicle-to-vehicle (V2V) communication were used by [16] to estimate the impacts of AVs. They found a 43% increase in capacity if all vehicles utilized sensors and V2V communication. An analytic and simulation-based approach was used to estimate the impacts of connection and automation [17]. They showed that CAVs had better capacity impacts than AVs at the same penetration rate. The influence of Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) on traffic flow was estimated in another study [18]. This study showed that CACC stabilized and improved capacity better than ACC. This was achieved through platooning which had better capabilities to streamline traffic. These studies did not include mixed traffic scenarios which limit their applications by transportation planners.

Mixed traffic (Autonomous and regular vehicles) cooperative and opportunistic platooning schemes were analyzed using average platoon length and the capacity of a mixed-traffic freeway [19]. The worst and best-case scenarios were considered for this study. Assuming a penetration rate of CAVs of 50% and using the most cautious possible platooning settings, a cooperative strategy could support 2806 vehicles per hour/lane. In contrast, an opportunistic strategy could support 2452 vehicles per hour/lane. This is a 31% and 14% increase over the previous maximum of 2142 vehicles per hour for a lane without platooning.

Penetration levels have been used in the literature to evaluate the impacts of AVs/CAVs. Capacity impacts for AVs/CAVs were evaluated using simulations on roundabouts [20]. Their results showed that penetration rates were correlated to capacity enhancements. They created capacity adjustment factors for use with the Highway Capacity Manual (HCM) values. Another study considered a mixed scenario of CAVs using a modified MIXIC (a microscopic simulation software) car-following model, to analyze interstate capacity in mixed traffic situations [21]. The results indicated a 28% increase in capacity owing to AVs and a 92% increase due to CAVs.

Other studies have also looked at different penetration levels and mixes of AVs/CAVs. A study worked on the potential impact of CAVs using different market penetration rates of 25%, 50%, 75%, and 100% to estimate the impacts of AVs [22]. Their study showed that delays will decrease for all levels of penetrations of AVs. In another study [23], the authors used different penetration rates of AVs to evaluate their impacts on roundabouts. The results also indicated that AV penetration levels will play a role in positively impacting transportation capacities. **Table 1** shows some key findings of the previous studies related to AV/CAV market penetration. However, these studies did not approach AV/CAV penetration from a long-range transportation planning perspective. Instead, they used fixed penetration rates which are important to consider in traffic operations. However, these studies do not provide the full picture for transportation planners to answer the AV/CAV impacts question based on their transportation plans which are typically time-based.

Table 1. Summary AV Penetration Literature.

Study	Study Type	AV Type/Penetration	Main Findings
[15]	Mathematical Model	CV and AV	• Deployment of AV lanes should be progressive rather than in one shot or radically • AV lanes should not be deployed until market penetration reaches a relatively high level • AV adoption rates will be positively impacted by annual cost, VOT for AV, and a higher number of annual trips by AVs and CAVs
[24]	Simulation	Mixed AV/CAV	• CAV penetration lower than 50% does not have a significant positive impact on dedicated lanes. Penetration higher than 80% will have a considerable impact.
[25]	Review	CV/AV/CAV	• 100% CAV increases freeway capacity by more than 100% • 100% AV increase freeway capacity by around 20%.
[26]	Accident Analysis	CAV	• 4.2% conflict reduction due to 10% penetration of CAV. • 17.4% conflict reduction due to 50% CAV • 43.4% conflict reduction due to 90% CAV

Study	Study Type	AV Type/Penetration	Main Findings
[27]	Review	AV	• Long-term private AV will reduce the use of public transport, parking areas, • The deployment path depends on socio-demographics, tech preferences, regulation, and liability.
[28]	Review	AV/CAV	• 40% or above AV penetration has a positive impact on traffic characteristics.
[29]	Review	AV	• Maximum greenhouse gas emission might take place within 60–80% of AV penetration.
[30]	Simulation	CAV/CV/AV	• 20% penetration is required of CAV for travel time improvement whereas AV needs 80%. • A mix of 60% CV and 20% CAV shows similar results as 80% AV for crash improvement.
[31]	Simulation	CAV/AV	• AV shows deteriorated situation over the network on low penetration as manual drivers are more aggressive. • CAV shows benefits to the network, but a low penetration rate has small negative results as they cannot share information with many vehicles.
[32]	Review	ACC, CACC, AV, CAV	• Market penetration will have a positive impact on traffic flow • Without connected vehicle technology, this impact is negligible • AV/CAV can result in reductions in emissions
[33]	Field Testing Experiment	CV, AV, CAV	• Small penetration of CV can yield benefits by reducing oscillatory traffic behavior

Moreover, in previous studies for capacity measurement of Basic Freeway Segment (BFS), Weaving, and Ramp junction, detector data were used to change the headway values for AV and CAV using a simulation model to estimate capacity [34]. The authors used real-world point data to obtain the Wiedemann calibration parameters for the traditional vehicle, but not for the AV or the CAV. Instead, they utilized headway values of 0.9 for the AV and 0.6 for the CAV. Using point data was a shortcoming for current models that predict the impacts of AVs/CAVs. Point data may misrepresent a study section by not considering varying driver speeds and driver behaviors at different points in a roadway section. Using trajectory data rather than point data will improve the ability of models to predict real-world conditions correctly.

Calibration and validation play an essential role in microsimulation model development. Also, choosing drivers' preferred speed distribution from unsaturated data is simple. Driver-selected speed distribution refers to driver-selected velocity in free-flow conditions on the freeway. Studies have used unsaturated to oversaturated traffic data with free-flow speed distribution [35][36][37][38]. However, a proper validation process is a shortcoming of those studies.

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