Effects of Connectivity and Automation on Saturation Headway and Capacity at Signalized Intersections

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Abstract
This paper analyzes the potential effects of connected and automated vehicles on saturation headway and capacity at signalized intersections. A signalized intersection is created in Vissim as a testbed, where four vehicle types are modeled and tested: (I) human-driven vehicles (HVs), (II) connected vehicles (CVs), (III) automated vehicles (AVs), and (IV) connected automated vehicles (CAVs). Various scenarios are defined based on different market-penetration rates of these four vehicle types. AVs are assumed to move more cautiously than HVs. CVs and CAVs are supposed to receive information about the future state of traffic lights and adjust their speeds to avoid stopping at the intersection. As a result, their movements are expected to be smoother with a lower number of stops. The effects of these vehicle types in mixed traffic are investigated in relation to saturation headway, capacity, travel time, delay, and queue length in different lane groups of an intersection. A Python script code developed by Vissim is used to provide the communication between the signal controller and CVs and CAVs to adjust their speeds accordingly. The results show that increasing CV and CAV market-penetration rate reduces saturation headway and consequently increases capacity at signalized intersections. On the other hand, increasing the AV market-penetration rate deteriorates traffic operations. Results also indicate that the highest increase (80%) and decrease (20%) in lane-group capacity are observed respectively in a traffic stream of 100% CAVs and 100% AVs.

Keywords
operations, traffic signal systems

Automated vehicles (AVs) are emerging with the promise of improving mobility and safety on highway facilities. Many research laboratories, vehicle manufacturers, and technology companies are currently researching and testing AVs on highway facilities. For instance, Waymo’s AVs have traveled about 10 million miles on public roads in 25 cities across the U.S. (1). Several car manufacturers, such as Tesla, Cadillac, and Audi, are building semi-automated commercial vehicles, while fully automated vehicles are expected to emerge by 2050 (2, 3).

Vehicle connectivity is also expected to be essential in improving mobility and safety (4–8). Current studies show that AVs are programmed to behave conservatively, perhaps to reduce the likelihood of severe crashes in the absence of information from other vehicles and obstacles that are not visible to the sensors of AVs (9, 10). Establishing dynamic communication among vehicles, infrastructure, and other wireless devices enables vehicles to collect real-time data and predict the future states of other users on the road more accurately. Consequently, this type of dynamic communication is expected to reduce the likelihood of crashes. As a result, connected AVs (CAVs) can drive more aggressively without increasing the risk of collision with other users (11). The advisory information also helps human drivers oversee upcoming traffic conditions and appropriately adjust their speed and maneuvers (12–19).

This study aims to understand the potential effects of connectivity and automation on traffic operations at signalized intersections. Existing studies have paid attention...
to the operations of automated and connected vehicles on freeway facilities (20–24). Still, the interaction of automated and connected vehicles with other vehicles and the signal controller has not received the same amount of attention (25). We have considered four types of connectivity/automation to account for different driving behaviors and their interactions in the traffic stream: (I) human-driven vehicles (HVs), (II) connected vehicles (CVs), (III) AVs, and (IV) CAVs. Various scenarios are examined for different market-penetration rates (proportion of each vehicle type in the traffic stream) of these vehicles.

The potential effects of CVs, AVs, and CAVs on intersection-level and lane-group-level saturation headway, travel time, delay, and queue length are studied using a simulated testbed created in Vissim. Full automation is assumed for both AVs and CAVs. These four aforementioned vehicle types are simulated by changing car-following model parameters in Vissim. Specifically, AVs receive information on their surrounding environment only from their onboard sensors and are assumed to operate with decision algorithms that are more conservative than HVs (10, 26). CVs are assumed to receive information about the future state of traffic lights and adjust their speeds to avoid stopping at the intersection. As a result, the movements of CVs are expected to be smoother with fewer stops. CAVs are assumed to combine all the capabilities of AVs and CVs. A Python script code developed by Vissim is used to model the communication between the signal controller, CVs, and CAVs to adjust their speed accordingly.

In the remainder of the paper, we first summarize the related literature and introduce the methodology. Then, the case study and numerical results are presented. The discussion of results is followed by concluding remarks and trends for future research.

**Literature Review**

The driving behavior associated with HVs, CVs, AVs, and CAVs differs by automation and connectivity level. Lower automation levels aim to assist human drivers through technologies enabled by onboard computers and sensors, such as adaptive cruise control (27), collision warning (28–30), collision avoidance (31), or assistant braking (32). On the other hand, higher automation levels enable AVs and CAVs to take complete control of the vehicle’s movements without any assistance from the human driver by predicting the future trajectory of surrounding vehicles and avoiding any potential collisions.

The interaction between vehicles with different levels of connectivity and automation will be a challenge in the near future since these vehicles have different driving behaviors (22). Currently, AVs are programmed to behave cautiously while interacting with HVs (33, 34). Human drivers require a higher reaction time to respond to any changes in the driving environment. Therefore, AVs need to consider various decision scenarios to overcome the uncertainty associated with human driver decisions (35). Sadigh et al. (33) showed that AVs could influence human driver behavior and yield a more efficient performance. Sezer et al. (36) also clarified that making AVs more aggressive could yield higher operating traffic volumes in a mixed-autonomy environment without compromising safety when there is communication between vehicles.

Connectivity can further improve the efficiency and reliability of automated systems (as well as human-controlled systems). Information sharing between vehicles and infrastructure increases the chance of reliable driving decisions, especially in relation to car following and lane changing (37). In addition, CAVs can improve traffic mobility without sacrificing safety. For instance, controlling the trajectory of CAVs upstream of signalized intersections based on advanced knowledge of signal phase and timing (SPaT) increases intersection throughput and reduces the experienced delay and risk of collisions among vehicles (29, 38–43). Moreover, the trajectory of CAVs can be managed to avoid stops at the intersection and minimize fuel consumption (13, 39, 44).

While many studies have examined the possible effects of connected and automated vehicles on traffic operations on uninterrupted flow facilities (20–24), the impacts of connectivity and automation on interrupted flow facilities, especially signalized intersections, are not thoroughly studied. Existing studies focus on either using signal-timing information to plan the arrival of CAVs (38–40), jointly optimizing signal-timing parameters and CAV trajectories (12, 45–49), or designing a signal-free environment with a fleet of 100% CAVs (50–60). The effects of different market-penetration levels of connectivity and automation on the saturation headway and capacity at signalized intersections are unknown. This study aims to fill this gap and provide insights into how a different mix of CVs, AVs, and CAVs in the traffic stream will influence saturation headway and capacity on signalized intersections.

**Methodology**

This study defines various driving behaviors in the Vissim simulation environment to represent HVs, CVs, AVs, and CAVs. Vissim is calibrated for the base condition representing a fleet of 100% HVs on an exclusive through-lane group. Different combinations of HV, CV, AV, and CAV market-penetration rates are created, and the saturation headway, along with delay, travel time, queue length, and throughput, are measured for each
scenario. The saturation headway values are used to fit a model of saturation headway as a function of HV, CV, AV, and CAV market-penetration rate, lane-group configuration, and turning percentage. The outcome of this model is used to determine capacity-adjustment factors (CAFs). Additional information is provided in the following sections.

**Vissim Simulation**

A microscopic simulation testbed is developed in Vissim to study the connectivity and automation technologies’ effects on traffic operations at signalized intersections. The simulation testbed provides the ability to consider various driving behaviors associated with connectivity and automation. Vissim allows the simulation of connected and automated vehicles and their interaction with conventional HVs. In addition, information exchange between vehicles and the infrastructure is modeled through Vissim’s Component Object Model (COM) interface. Finally, Vissim provides various outputs ranging from vehicle-level output to network-level performance measures.

**Driving Behavior**

The driving behavior of vehicles with full automation is adopted from existing practical studies on the behavior of AVs. In particular, the findings of the CoEXist project are used to simulate the movement of AVs in Vissim. The recommendations of the CoEXist project are based on the empirical analysis of data collected in the Netherlands. The experimental results are confirmed by Vedecom Tech and several simulation tests done by the PTV Group (21).

**Car-Following Behavior.** The CoEXist project recommended three variants of driving models: (1) CoEXist cautious model, (2) CoEXist normal model, and (3) CoEXist all-knowing model (21). The cautious driving behavior respects the road code and always ensures moving safely on the road. There is always a brick wall distance between a cautious-driving vehicle and its immediate leading car. This means that if the leading vehicle comes to an instantaneous stop, the cautious-driving vehicle can stop as well and avoid a crash. In addition, a large gap is required to perform a lane change maneuver or pass an unsignalized intersection. The normal driving behavior is very similar to the behavior of a human driver, with the additional capacity to measure distances and speeds of surrounding vehicles by collecting information from sensors. All-knowing driving behavior assumes a perfect perception of the surrounding environment and receives vehicle-to-vehicle and vehicle-to-infrastructure communications. This driving behavior is associated with smaller gaps for all maneuvers. In this study, the movement of AVs is assumed to follow the CoEXist cautious model, while the movement of CAVs is assumed to follow the CoEXist all-knowing model. The movement of HVs and CVs follows normal driving behavior with a difference in the following behavior variability, which is smaller for CVs. The signal-timing information is shared with CVs and CAVs. As a result, the driving behavior of vehicles under these two types will be different from the cases in which the information is not received, as follows in the next section. Table 1 summarizes the calibrated components of Wiedemann 99 car-following parameters adopted from the CoEXist project.

**Signal Control Behavior.** When no information is available about the future signal-timing plan at an intersection, vehicles either follow their lead vehicles or travel at their desired speed. They will go through the intersection if they hit the green signal; otherwise, they stop at the red light. Sharing signal-timing information with upcoming

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Definition</th>
<th>HV</th>
<th>CV</th>
<th>AV</th>
<th>CAV</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC0</td>
<td>Stand still distance (m)</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1</td>
</tr>
<tr>
<td>CC1</td>
<td>Headway time (s)</td>
<td>1.6</td>
<td>1.6</td>
<td>2.2</td>
<td>1</td>
</tr>
<tr>
<td>CC2</td>
<td>Following variation (m)</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>CC3</td>
<td>Threshold for entering following (s)</td>
<td>-8</td>
<td>-8</td>
<td>-10</td>
<td>-6</td>
</tr>
<tr>
<td>CC4</td>
<td>Negative following threshold (m/s)</td>
<td>-0.35</td>
<td>-0.35</td>
<td>-0.1</td>
<td>-0.1</td>
</tr>
<tr>
<td>CC5</td>
<td>Positive following threshold (m/s)</td>
<td>0.35</td>
<td>0.35</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>CC6</td>
<td>Speed dependency of oscillation (1/(m/s))</td>
<td>11.44</td>
<td>11.44</td>
<td>0</td>
<td>0</td>
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<tr>
<td>CC7</td>
<td>Oscillation acceleration (m/s²)</td>
<td>0.25</td>
<td>0.25</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>CC8</td>
<td>Standstill acceleration (m/s²)</td>
<td>3.5</td>
<td>3.5</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>CC9</td>
<td>Acceleration with 50 mph (m/s²)</td>
<td>1.5</td>
<td>1.5</td>
<td>1.2</td>
<td>2</td>
</tr>
</tbody>
</table>

Note: HV = human-driven vehicles; CV = connected vehicles; AV = automated vehicles; CAV = connected automated vehicles.

Table 1. Wiedemann 99 Car-Following Model Calibration Components (CC) (21)
vehicles can change their driving behavior as they approach the intersection. Table 2 shows Vissim’s car-following behavior for different connectivity and automation levels as vehicles arrive at an intersection. HVs and AVs must continuously check the signal-timing status during the yellow time to avoid red-light violations. Although CVs receive the signal-timing plans, the human driver still needs to check to ensure safe entrance to the intersection constantly. On the other hand, CAVs receive information on future signal-timing plans and do not need to check them continuously. In addition, the safety factor for AVs and CAVs is considered higher to ensure no collision will occur with other vehicles at the intersection.

Other Behaviors. Other driving behavior parameters suggested by the CoEXist project are shown in Table 3. Enforce absolute braking distance (EABK) is active for AVs since they drive cautiously on the road. Based on EABK, a further gap between the following and leading vehicles is maintained to allow AVs to stop safely anytime, even if the lead vehicle stops instantly. Vissim does not consider any stochasticities associated with AVs. CAVs can interact with more than one vehicle in the traffic stream, but non-CAVs interact with the most immediate vehicle.

Vissim Calibration

Wiedemann’s 99 car-following model is selected because it can model both AVs and CAVs (21). The main reason for using this model is that the model parameters for AVs and CAVs are found for this model and not Wiedemann’s 74 car-following model. Model parameters are calibrated to match the saturation headway. The headway depends on two main factors in Vissim: (1) the desired speed and (2) the car-following characteristics. The desired speed is defined as the speed vehicles use in free-flow conditions. Since the desired speed is assumed fixed for all vehicle types, only the car-following parameters should be calibrated. As shown in Table 1, the Wiedemann 99 car-following model contains 10 parameters. However, only two parameters (i.e., CC0 and CC1) influence the intersection headway significantly (61). CC0 is the average desired distance between two vehicles in meters at a standstill while queuing before the traffic signal. The headway (CC1) describes the speed-dependent part of the safety distance a driver desires. Therefore, various combinations of these two factors are tested to calibrate the model.

Advisory Speeds

CVs and CAVs can adjust their speeds based on the received information on future signal-timing plans to smoothen their movement and arrive at the intersection during the green signal. This research utilizes a Python script code developed by the PTV Group to allow communications between the signal controller and CVs and CAVs. The script adjusts the minimum and maximum speed required to arrive at the intersection during a green light. If the minimum speed is less than the desired speed, the vehicle moves with the desired speed; otherwise, a constant smooth speed will be provided. It should be

<table>
<thead>
<tr>
<th>Attribute</th>
<th>HV</th>
<th>CV</th>
<th>AV</th>
<th>CAV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Behavior at the amber signal</td>
<td>Continuous</td>
<td>Continuous</td>
<td>Continuous</td>
<td>One decision</td>
</tr>
<tr>
<td>Behavior at red/amber signal</td>
<td>Go</td>
<td>Go</td>
<td>Stop</td>
<td>Stop</td>
</tr>
<tr>
<td>Reduced safety distance factor</td>
<td>0.6</td>
<td>0.6</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Reduced safety start upstream of stop line (m)</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Reduced safety end upstream of stop line (m)</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Note: HV = human-driven vehicles; CV = connected vehicles; AV = automated vehicles; CAV = connected automated vehicles.

<table>
<thead>
<tr>
<th>Driving logic</th>
<th>Enforce absolute braking distance</th>
<th>Use implicit stochastics</th>
<th>Number of interaction vehicles</th>
<th>Increased desired acceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td>HV</td>
<td>OFF</td>
<td>ON</td>
<td>1</td>
<td>100%–110%</td>
</tr>
<tr>
<td>CV</td>
<td>OFF</td>
<td>ON</td>
<td>1</td>
<td>100%</td>
</tr>
<tr>
<td>AV</td>
<td>ON</td>
<td>OFF</td>
<td>1</td>
<td>100%</td>
</tr>
<tr>
<td>CAV</td>
<td>OFF</td>
<td>OFF</td>
<td>&gt;1</td>
<td>110%</td>
</tr>
</tbody>
</table>

Note: HV = human-driven vehicles; CV = connected vehicles; AV = automated vehicles; CAV = connected automated vehicles.
noted that the constant speed needs to be higher than a
certain amount to avoid crawling. Vissim’s default value is
5 mph, which is used in this study. Similarly, the maximum
speed to the intersection is calculated and compared with the
desired speed. If the maximum speed exceeds the
desired speed, the desired speed will be used. Otherwise,
the maximum speed is considered the optimal speed for
arriving at the intersection during the green signal.

**Saturation Headway and Capacity-Adjustment Factors**

The saturation headway is defined as the average headway
between the fourth and tenth passenger cars in the
queue when the traffic light changes from red to green.
The headways are quantified using a script that analyzes
the trajectory of vehicles and determines the exact time
their front bumpers hit the stop line. This approach is
based on Chapter 6 of the ITE Manual of Transportation
Engineering Studies (MTES) (62). The estimated saturation
flow rate from field data is defined as the number of
vehicles that pass the stop bar at the intersection with no
interruptions in a defined period. Based on the MTES
approach for collecting saturation-flow-rate data, a timer
is started when the fourth vehicle in a queue passes the
stop bar; at that point, the queue typically begins main-
taining consistent headway after any incurred start-up
lost time. The timer is stopped when either the seventh,
eighth, ninth, or tenth vehicle passes the stop bar, which-
ever is the last in the stopped queue. For a typical stan-
dard deviation in saturation flow rate of 140 vehicles per
hour (vph), the MTES suggests observing a minimum of
30 valid queues to estimate the mean saturation flow rate
of 10% passenger cars would be excluded from this
analysis to avoid confounding effects. Saturation head-
way data is aggregated at the 15 min period to be consis-
tent with the 15 min analysis period of the Highway
Capacity Manual (HCM) (63).

A regression approach can use either additive or mul-
tiplicative models to predict saturation headway. This study
employs additive models because of their simplicity and
consistency with HCM. In additive models, the base
saturation headway (all HVs on the exclusive through-lane
group) is adjusted by subtracting or adding values corre-
spending to different market-penetration rates of CVs,
AVs, and CAVs. In addition, the saturation headway is
adjusted for exclusive right-or left-turn lanes. The inter-
cept ($h_s$) represents base saturation headway, and the
dependent variable ($h_s^{adj}$) represents adjusted saturation
headway under a combination of CVs, AVs, and CAVs.

$$h_s^{adj} = h_s + \beta_1(CV) + \beta_2(AV) + \beta_3(CAV) + \beta_4(D_{EXL})$$
$$+ \beta_5(D_{EXR}) + \beta_6(D_{SHTR}) + \beta_7(D_{SHTR})(RT)$$  \(1\)

where

- $h_s^{adj}$ = adjusted saturation headway (seconds),
- $h_s$ = base saturation headway for non-work zone
  conditions,
- CV = market-penetration rate of CVs in real
  numbers,
- AV = market-penetration rate of AVs in real
  numbers,
- CAV = market-penetration rate of CAVs in real
  numbers,
- $D_{EXL}$ = exclusive left-turn lane (0: no, 1: yes),
- $D_{EXR}$ = exclusive right-turn lane (0: no, 1: yes),
- $D_{SHTR}$ = shared through-and-right lane group (0: no, 1: yes), and
- RT = right-turn percentage on shared lanes (%).

The capacity of each lane group is a function of the
saturation headway, effective green, and cycle length as follows:

$$c = \left(\frac{3600}{h_s}\right)\left(\frac{g}{C}\right)$$  \(2\)

where

- $c$ = capacity (passenger cars per hour per lane),
- $g$ = effective green (seconds), and
- $C$ = cycle length (seconds).

Therefore, the adjusted capacity $c^{adj}$ can be deter-
mined using

$$c^{adj} = \left(\frac{3600}{h_s^{adj}}\right)\left(\frac{g}{C}\right)$$  \(3\)

Assuming the signal-timing parameters are unchanged
in the presence of CVs, AVs, and CAVs, CAFs can be
determined as

$$CAF = \frac{c^{adj}}{c} = \frac{h_s}{h_s^{adj}}$$  \(4\)

Note that CAF can be larger than 1, as a fleet of 100%
CAVs is expected to increase the capacity.

**Intersection Testbed**

Figure 1 shows the layout of the intersection testbed used
in this research. The testbed includes various lane groups.
The eastbound approach has exclusive left-turn, through,
and right-turn lane groups. Other approaches include a
shared right-turn-and-through lane group. Fixed-time
signal timing is used, and the signal-timing parameters are
optimized using Vistro (64). The demand for the east-
bound entry is 900 vph, and the demand for other
approaches is 1,200 vph. The turning percentage for left-
turn movement is 15% for all approaches. The right-turn
percentages for eastbound, northbound, westbound, and
southbound are assumed to be 15%, 5%, 15%, and 25%, respectively. Six different market-penetration rates for CVs, AVs, and CAVs are simulated: 0%, 20%, 40%, 60%, 80%, and 100%. For instance, a scenario can have 20% HVs, 20% CVs, 40% AVs, and 20% CAVs. In total, 56 scenarios are considered. Each scenario is run 10 times with different random seeds to account for randomness.

Results

Lane-Group-Level Analysis

Saturation Headway. Figure 2 shows the saturation headway of CVs, AVs, and CAVs compared with the base case, that is, 100% HVs (shown as 0% penetration rate in the figure). The results are shown for exclusive right-turn, through, and left-turn lane groups. Increasing the market-penetration rate of CVs and CAVs decreases the saturation headway for all exclusive lanes. This trend could be attributed to having access to advanced information about the future signal plan of the traffic light. As a result, CV drivers are ready to move with shorter start-up lost time and reaction times. CAVs have shorter saturation headway than CVs because of the lower levels of uncertainty associated with the absence of human driving.

In contrast to CVs and CAVs, a higher penetration rate of AVs is associated with an increase in saturation headway. This trend is primarily because AVs are programmed to travel more cautiously near the intersection to avoid collisions. As expected, the saturation headway is lower on exclusive through lanes than on exclusive left- and right-turn lanes because vehicles need to slow down to negotiate the curve.

A similar analysis is performed for shared right-turn-and-through lanes. The trends are similar to exclusive right-turn lanes. However, different right-turn percentages do not substantially affect the saturation headway in the shared right-and-through lanes.

Multi-linear regression analysis predicts the saturation headway as a function of CV, AV, and CAV market penetration and lane configuration. The base condition in this model is having an exclusive through lane with 100% HVs. Indicator variables specify different lane configurations corresponding to the exclusive left-, exclusive right-, and shared through-and-right-turn lanes. The shared-through-and-right-turn-lane coefficient was close to zero and had a large p-value (>0.85). Therefore, it was removed from the model. Table 4 presents the final model results, and Equation (5) presents the estimated model.

\[
h_{S}^{\text{adj}} = 1.95 - 0.51(\text{CV}) + 0.56(\text{AV}) - 0.91(\text{CAV}) + 0.11(D_{\text{EXL}} + D_{\text{EXR}}) \tag{5}
\]

The model is associated with an adjusted R-squared value of 0.926 and passes the multi-linear regression assumptions. All the estimated model parameters are intuitive and have reasonable values. The model’s intercept in the base condition is 1.95, which means that the saturation headway in an exclusive through lane with 100% HVs is 1.95 s. The saturation headway decreases with an increase in the CV market-penetration rate. Each additional percentage point of CVs reduces the saturation headway by 0.0051 s. The opposite is found for AVs, for which each additional percentage point increases saturation headway by 0.0056 s. As expected, CAVs reduce the saturation headway. The model also suggests that the saturation headway in exclusive right-or left-turn lanes is 0.11 s longer than in an exclusive through lane, regardless of the CV, AV, and CAV market-penetration rate. The model helps estimate the saturation headway for a combination of CV, AV, and CAV market-penetration rates. For instance, the saturation headway on an exclusive through lane with 10% HVs, 15% CVs, 25% AVs, and 50% CAVs can be calculated as 1.95 - 0.51(0.15) + 0.56(0.25) - 0.91(0.5) = 1.59 s. While the model has a high adjusted R-squared value and the parameters are reasonable and follow our initial expectations, the output values of the model should be used cautiously. The main reason is that this study implements assumptions and changes, informed by the literature, in specific parameters of Vissim’s car-following and lane-changing models, which were designed to represent human driving behavior. The primary purpose of the model is to illustrate trends.

The fitted model is used to visualize the effects of CV, AV, and CAV market-penetration rates on saturation

Figure 2. Case study intersection.
headway in exclusive-through-lane groups. Figure 3 shows four heatmaps for 0%, 20%, 40%, and 60% HV market-penetration rates in parts (a) through (d), respectively. The x-axis shows the CAV market share, the y-axis shows the AV market share, and the CV market share is found by CV = HV / (C0 / AV) / CAV, where HV represents the human-driven vehicle market share. The trends are as expected: an increase in the CAV market share decreases the saturation headway, while the opposite trend is observed for AVs. Note that only in part (a), where the HV market share is zero, can the market share of CVs, AVs, and CAVs reach 100%.

**Capacity-Adjustment Factors.** The CAF can be found using Equation (6). This equation is directly found by dividing the base saturation flow rate by the adjusted saturation flow rate when CVs, AVs, or CAVs are present in the traffic stream. Note that any combination of market-penetration rates can be entered into the equation as long as the market-penetration rates of HVs, CVs, AVs, and CAVs add up to 1.

\[
CAF = \frac{h_s}{h_{s\text{adj}}} = 1.95(1.95 - 0.51(CV) + 0.56(AV) - 0.91(CAV) + 0.11(D_{\text{EXL}} + D_{\text{EXR}}))^{-1}
\]

Similar to the previous section, the equation is used to visualize the effects of CV, AV, and CAV market-penetration rates on CAFs (see Figure 4). Not CV = 1 – HV – AV – CAV that it is assumed that the signal-timing parameters are unchanged in the presence of connected and automated vehicles, and the change in capacity is only a result of changes in saturation headway. Increasing the market-penetration rate of CVs and CAVs increases the capacity of lane groups. In contrast, more AVs decrease the capacity and bring it below the base capacity when only HVs are present in the traffic stream.

**Average Delay.** In addition to saturation headway, the average delay of vehicles for each lane group under different market-penetration rates and lane configurations is determined. Figure 5 shows that increasing the market-penetration rate of CVs and CAVs leads to decreasing delay. On the other hand, increasing the AV market share increases the delay because of AVs’ cautious driving behavior in the vicinity of the intersection. A significant increase in average delay on the exclusive-through-lane group is observed when the market-penetration rate of AVs goes from 80% to 100%. The main reason for this steep increase is that the capacity of this lane group
Figure 3. Saturation headway (in seconds) for different CV, AV, and CAV market-penetration rates on exclusive through lanes.
Note: CV = connected vehicle; AV = automated vehicle; CAV = connected automated vehicle; HV = human-driven vehicle; and CV = 1 – HV – AV – CAV.

Figure 4. Capacity-adjustment factor for different CV, AV, and CAV market-penetration rates on exclusive through lanes.
Note: CV = connected vehicle; AV = automated vehicle; CAV = connected automated vehicle; HV = human-driven vehicle; and CV = 1 – HV – AV – CAV.
falls below the incoming volume when the AV market-penetration rate reaches 100%.

Figure 6 shows the average delay of vehicles in shared lanes with different turning percentages. Similar trends are observed: increasing the market-penetration rates of CVs and CAVs decreases the average delay while increasing the AV market share is associated with an increase in the average delay. These trends are as expected and are a direct result of the trends observed before in respect of the effects of CVs, AVs, and CAVs on saturation headway and capacity.

Queue Length. Figure 7 shows the average queue length for each lane group of the intersection. Increasing the market-penetration rate of CVs and CAVs decreases the average queue length for all lane groups. The reduction rate is more substantial for through movements since they have higher demand volumes. On the other hand, increasing the market-penetration rate of AVs results in a higher queue length, primarily because of the longer headways that AVs maintain compared with other vehicle types. We also observe that the queue lengths for southbound through (SBT) and southbound right (SBR) lane groups are longer than others because of high right-turning percentages (i.e., 25% right turn).

Intersection-Level Analysis

In addition to the lane-group-level analysis, we analyze the effects of connectivity and automation on mobility performance measures at the intersection level. Figure 8 shows the average delay for the entire intersection.
Increasing the penetration rate of CVs and CAVs decreases the average delay. However, increasing the AV penetration rate increases the average delay at the intersection. We observe that the lowest delay is associated with the highest number of CAVs in the intersection. Similar trends are also observed for the intersection average travel time, shown in Figure 9.

Based on the results shown in Figure 10, increasing the penetration rate of CVs and CAVs increases the intersection throughput slightly. However, increasing the AV penetration rate decreases intersection throughput substantially, which may be a result of a reduction in intersection capacity. The maximum throughput for 1 h of the simulation was 4,375 vph, with 100% CAVs in the traffic stream. On the other hand, the lowest throughput was 3,763 vph associated with 100% AV in the traffic stream.

Figure 11 shows heatmaps for intersection-level saturation headway for different CV, AV, and CAV market shares. The trends follow the previous observations for saturation headway on other lanes (see Figure 3 for trends on exclusive through lanes). Increasing the market-penetration rate of AVs increased the saturation flow rate, whereas increasing the market share of CAVs reduced it, at the intersection level. Figure 12 shows the aggregated average saturation headway in the intersection. The saturation headway of human drivers was equal to 2 s, which was achieved by the calibration process. Increasing the CV market-penetration rate decreased the average saturation headway to 1.5 s, representing a 25% reduction, whereas increasing the AV market-penetration rate increased it to 2.6 s, representing a 30% increase. CAVs moved more efficiently through the intersection.

Figure 7. Average queue length for all movements of the intersection.

Note. CVs = connected vehicles; AVs = automated vehicles; CAVs = connected automated vehicles; WB = westbound; SB = southbound; NB = northbound; EB = eastbound; R = right turning; T = through; L = left turning.
Figure 8. Intersection-level average delay.
Note. CV = connected vehicle; AV = automated vehicle; CAV = connected automated vehicle.

Figure 9. Intersection-level average travel time.
Note. CV = connected vehicle; AV = automated vehicle; CAV = connected automated vehicle.

Figure 10. Intersection throughput.
Note. veh = vehicles; CV = connected vehicle; AV = automated vehicle; CAV = connected automated vehicle.
with 1.2 s of saturation headway, indicating a 40% reduction compared with the base scenario.

**Conclusion**

This study evaluates the potential effect of a mixed traffic stream of human-driven, automated, and connected vehicles on saturation headway and capacity at signalized intersections. Previous studies mainly focused on the operation of connected or automated vehicles on freeway facilities. However, the information received on future signal-timing plans can significantly affect the behavior of CVs, AVs, and CAVs in signalized intersections. Four vehicle types are considered as (I) HVs, (II) CVs, (III)
AVs, and (IV) CAVs. Vissim is used as a testbed to simulate the movement of vehicles with different driving behaviors and study their potential effects on mobility when they interact with each other and traffic signal controllers under various market-penetration rates.

The results show that CAVs provide the most efficient mobility. CVs also improve mobility as a result of receiving information about future signal-timing plans. Both CVs and CAVs can adjust their speed upstream of the intersection to arrive at the green traffic light. In contrast with CVs and CAVs, AVs drive more cautiously and yield longer saturation headways and delays. Results also show that the highest increase (80%) and decrease (20%) in lane-group capacity are observed, respectively, in a traffic stream of 100% CAVs and 100% AVs.

This study determines saturation headway and CAF for different lane groups under various CV, AV, and CAV market-penetration rates. These values could be used to calculate the saturation flow rate and capacity of various lane groups in the presence of vehicles with full automation or connectivity capabilities. Both saturation headway and CAF are applicable to fixed-time and actuated controlled intersections. Note that the changes observed in capacity are solely caused by the changes in saturation headway (as a result of different market-penetration rates of CVs, AVs, and CAVs) as signal-timing parameters remained fixed in all scenarios.

The results of this research can be used by transportation agencies to predict the impacts of connectivity and automation on local and regional traffic. This information is essential for long-range transportation plans that must consider how to better prepare for the future and prevent or mitigate any adverse effects from emerging vehicle technologies. This study implements assumptions and changes, informed by the literature, in certain parameters of Vissim’s car-following and lane-changing models, which were originally designed to represent human driving behavior. Further studies are required to replace existing simulation packages’ car-following and lane-changing logic with logic specifically designed for CVs, AVs, and CAVs. In addition, this study assumes conservative behavior for AVs. However, it is possible that manufacturers will design AVs to operate less conservatively as the market penetration increases and the technology matures. Future studies can explore the potential changes in AV behavior over time and its implications for the capacity of signalized intersections.

**Author Contributions**

The authors confirm contribution to the paper as follows: study conception and design: Ali Hajbabaie; data collection: Ali Hajbabaie, Mehrdad Tajalli; analysis and interpretation of results: Ali Hajbabaie, Mehrdad Tajalli; draft manuscript preparation: Ali Hajbabaie, Mehrdad Tajalli, Eleni Bardaka. All authors reviewed the results and approved the final version of the manuscript.

**Declaration of Conflicting Interests**

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Funding**

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This paper presents results from a larger project funded by the North Carolina Department of Transportation (NCDOT) titled “Impacts of Autonomous Vehicle Technology on Transportation Systems”; see (9, 11, 26).

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