Traffic Efficiency and Safety Impacts of Autonomous Vehicle Aggressiveness

Dr. Songpo Li, Corresponding Author
Postdoctoral Associate
Humans and Autonomy Lab
Department of Electrical and Computer Engineering,
Duke University, North Building, Room 139, 304 Research Drive, Durham, NC, 27708
Email: Songpo.li@duke.edu

Dev Seth
Trinity College
Duke University, Durham, NC, 27708
Email: dev.seth@duke.edu

Prof. Mary L. Cummings
Humans and Autonomy Lab
Department of Electrical and Computer Engineering,
Duke University, North Building, Room 131, 304 Research Drive, Durham, NC, 27708
Email: mary.cummings@duke.edu

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ABSTRACT

Great attention has been given to feasibility research on safe operation of autonomous vehicles, especially in light of developments in perceptual and decision-making capabilities. However, due to a number of safety concerns, autonomous vehicles are often programmed to be overly conservative when interacting with human-driven vehicles. Autonomous vehicles are expected to be safer than human-driven vehicles given that they are immune to inebriation, carelessness, tiredness, and distraction. Given that autonomous vehicles may have faster response times and more precise control, behaviors traditionally considered aggressive for human drivers may be viable for autonomous vehicles, such as short following distances and closer lane changing, among others. Moreover, there may be scenarios where autonomous vehicles need to be aggressive to deal with emergencies or to interact with unfriendly or aggressive human drivers. To this end, we investigated how autonomous vehicle fleets with various aggressive levels of driving would impact traffic. A highway section was simulated within PTV VISSIM, a microscopic traffic flow simulation software, and four existing models of autonomous vehicles were tested for their impact on traffic flow efficiency and safety. Our results revealed that overly cautious AVs could pose new risks to traffic efficiency and safety. Future work may improve granularity of the results by separately evaluating advanced capabilities and driving styles for AVs.

Keywords: Autonomous vehicles, driverless car, aggressive driving, autonomous vehicles models, simulation.

INTRODUCTION

With extensive attention given to autonomous vehicles (AVs) from research laboratories, vehicle manufacturers, and technology companies, significant advancements have been made in AV technology in the last few years. In 2018, Waymo AV's traveled 10 million miles on public roads in 25 cities across the US (*1*), and commercial vehicles with semi-autonomous capabilities are now offered by Tesla, Cadillac, and Audi (*2*). Such advancements have led to very favorable attitudes towards such systems in some settings. For example, in one study, twenty experts predicted that between 7% and 61% of the vehicle fleet would be fully automated by 2050 in the Netherlands (*3*). Similarly, in another public survey across 109 countries, 69% of responders estimated that fully automated driving would reach a 50% market share between now and 2050 (*4*).

Within AV research, safety has been a stated top consideration. In order to safely navigate in complex traffic, AVs are typically programmed to be overly conservative (*5*). Currently, experimental AVs are very conservative while interacting with other human-driven vehicles for lane changes and intersection crossings (*6*-*8*). However, conservative AV behavior is not always desirable or necessary, given potential consequences like low efficiency and uncomfortable traveling experiences. Some researchers have also pointed out that aggressive driving for AVs is desirable in many cases like reconnaissance, material transport, emergency handling, efficiency-sensitive application, or simply due to human preference (*5, 9*-*11*). This has prompted research into AV driving behavior, and more work is looking at AV aggressive maneuvering while ensuring driving safety (*6, 12*).

Towards this end, we investigate how simulated AV fleets with varying aggressive driving behaviors could affect overall traffic efficiency and safety. It extends current research on AV aggressive driving by building from the microscopic level, whereby individual AV aggressive maneuvers are aggregated at the macroscopic level allowing for investigation of the impact of aggressive AVs. In order to accomplish this, a highway section was built in the PTV VISSIM traffic flow simulation software, and four existing models of AVs were adopted with various aggression levels. On the simulated highway section, traffic with different mixture ratios of AVs and human-driven vehicles (HDVs) were tested for traffic flow efficiency and safety.

RELATED WORK

Due to complex human behaviors and unobservable internal states, various researchers have defined aggressive driving differently. In (*13*), Tasca proposed the definition as "A driving behavior is aggressive if it is deliberate, likely to increase the risk of collision and is motivated by impatience, and annoyance, hostility, and/or attempt to save time." Definitions from other researchers are similar but with differing emphases. In (*14*), selfish, pushy, and impatient manners were highlighted in the definition, while (*15*) contends any unsafe and deliberate driving behaviors constitute aggressive driving. Moreover, two types of aggressiveness have been identified as contributors to aggressive driving behaviors, namely state and trait aggressiveness (*16*). State aggressiveness includes those aggressive behaviors that are provoked by extraneous factors such as congestion, red lights, or behaviors of other drivers or pedestrians. In contrast, trait aggressiveness is a result of a driver's internal driving state, i.e., a driver may be aggressive by nature. In (*17*), the authors used the self-determination theory to develop a motivational model of driving anger and aggression by studying 111 individuals' 10-day driving records.

So, while there are different opinions about what constitutes aggressive driving, there is no consensus about what defines aggressive driving. Recent technology advances in perception, reasoning, and control could enable AVs to interact with their surroundings more quickly and precisely (*18*). Such maneuvers could be seen as aggressive. Indeed, there have been instances of where optimal AV driving behavior makes human passengers uncomfortable due to perceived aggressiveness. In one case, AVs made early right turns, which were legal and safe, but humans perceived such turns as overly aggressive (*19*).

Researchers have been investigating AV aggressive driving, and one such study (*20*) examined aggressive maneuvers on sloped terrain via a model predictive control (MPC) framework that explicitly considered the terrain geometry for path tracking. In (*21*), the authors used professional racing car driver testing data to analyze vehicle dynamic stability and agility of human-controlled aggressive vehicle maneuvers. This led to a hybrid physical-dynamic friction model to capture complex tire-road interactions, which resulted in an accurate dynamic model informing the design of a sophisticated motion planner and controller. In (*22*), a proportional-derivative controller and a quadratically optimal iterative learning controller were developed for coping with the highly nonlinear steering dynamics and modeling difficulty of tires. Both controllers were tested on an autonomous Audi TTS and were able to correct transient path tracking errors and achieve better performance relative to a reference feedforward controller used in their previous study (*23)*.

Others have studied aggressive driving with model predictive control, conventional neural networks, and reinforcement learning (*24*-*26*). In (*27*), the authors studied the interaction dynamics between vehicles and found that AVs could leverage other vehicles' actions to plan for more efficient and communicative behaviors. The decision-making process of crossing unsignalized intersections was modeled in (*28*) for AVs, and AVs aggressive level could be regulated with a pre-defined parameter to maximize traffic flow.

What has not been studied in the published literature is how such AV aggressiveness could impact overall traffic flow and aggregate safety projections. Many people have claimed that a significant advantage of AVs over HDVs is that AVs could help reduce congestion and improve mobility, which ultimately would benefit overall safety (*29*-*32*). So, to determine whether such benefits could exist, we modeled different levels of AV aggressiveness in simulated highway settings to generate preliminary estimates of any changes in traffic flow.

METHODS

Simulation Environment

A highway section from Durham, NC was created in VISSIM software from the PTV Group. VISSIM is a microscopic traffic flow simulator in which each entity (car or person) is simulated individually with a high level of granularity. Simulations of microscopic traffic flow are a powerful tool for studying traffic flow (*33*-*34*). Owing to its vast array of functions and flexibility in modeling diverse scenarios, VISSIM has been widely used to simulate various traffic conditions for traffic safety examinations (*32, 35*). The simulated highway section used in this study is shown in **Figure 1**, where traffic comes in from the lower right and passes to the upper left, so only one side of the highway was modeled. There were straight sections at both ends of the highway, not displayed here. This section was chosen specifically to allow multiple opportunities for manifestation of differences in driving behavior, to allow for a more in-depth comparison of the driving models. At location 1, a lane was dropped, and there was an exit ramp at location 2. There were merge and split junctions at location 3. These locations represent potential conflict points where aggressive moves may be needed as vehicles change lanes or cooperate with vehicles attempting to execute lane changes.

The times taken for simulated vehicles to travel through four road segments on the highway were recorded for moderate and high traffic volumes, described in detail in a later section. The first segment was from the beginning to the end of this highway section for vehicles that passed this highway section with a segment length of 2600m. The second segment (length 250m) was from **a** to **d** for vehicles that exited the off-ramp. The segment from **c** to **e** (length 229m) was the third one for vehicles that entered the highway using the on-ramp. The last time measure was from **b** to **f** (length 371m) for vehicles passing through the on-ramp and off-ramp. In conjunction with these traffic efficiency time measures, highway safety was also evaluated using Surrogate Safety Assessment Model (SSAM) (*36*-*37*). SSAM is an open-source software application developed by the U.S. Department of Transportation to estimate traffic conflicts from vehicle trajectories output from microscopic traffic simulation models like VISSIM. A traffic conflict is a scenario where two road users will likely collide without evasive actions, which is a strong indicator of actual crashes and can be estimated by examining the two vehicles' trajectories.

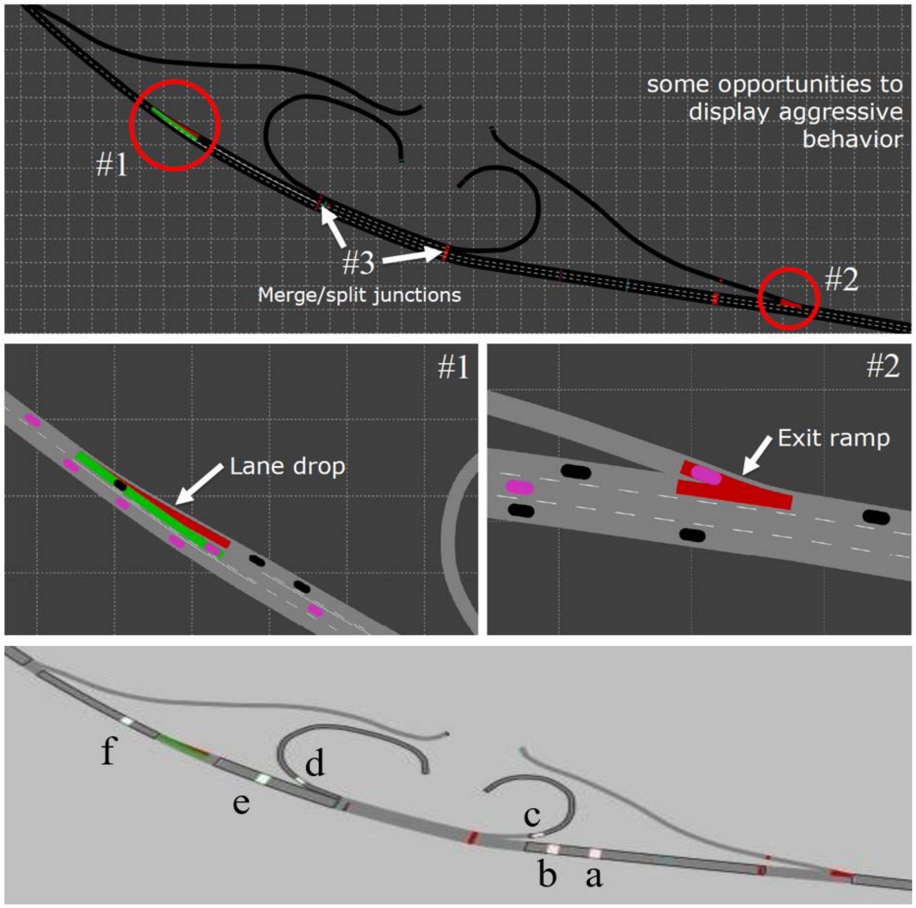


Figure 1 The highway section of the simulation environment in VISSIM.

AV Driving Models

AV models from two established teams, CoEXist and Fehr & Peers, were adopted in our study. The CoEXist AV model is the default AV model in VISSIM and was jointly developed by the CoEXist project, funded by the European Union's Horizon 2020 Programme. The CoEXist model had three variants, the CoEXist normal model, CoEXist cautious model, and CoEXist all-knowing model (*38*-*39*). The driving model of the CoEXist cautious model respects the rules of the road and always adopts safe behaviors. CoEXist normal vehicles are very similar to HDVs with the additional capability of measuring and maintaining distances and speeds of the surrounding vehicles due to the onboard sensors. All-knowing AVs are assumed to be equipped with perfect perception and prediction, as well as turns to maintain smaller gaps for all maneuvers and situations. The second model, the Fehr & Peers model, was developed by researchers from Fehr & Peers Transportation Consultants based in California US (*40*). Both models follow the same Wiedemann 99 car following model (*41*) and lane change model, as do traditional HDVs in VISSIM for freeway driving.

The parameters of the CoEXist models have been calibrated using real-world data collected from a public test track through the CoEXist project (*38*-*39*), and parameters of Fehr & Peers were proposed based on experience (*40*). The default model for HDVs from VISSIM was used in this study (*40*). **Table 1** and **Table 2** summarize the parameters taken for each model, and more information about each parameter can be found in (*40*).

TABLE 1 Vehicle Following Parameters – Wiedemann 99 Model. CC stands for calibration component.

Parameter	Human-driven	Fehr & Peers	CoEXist normal	CoEXist cautious	CoEXist all-knowing
CC0 – Standstill distance (ft)	4.92	4.10	4.92	4.92	3.28
CC1 – Headway time (seconds)	0.9	0.25	0.9	1.5	0.6
CC2 – Car-following distance/following variance (ft)	13.12	9.84	0	0	0
CC3 – Threshold for entering following (s)	-8	-12	-8	-10	-6
CC4 – Negative following threshold (ft/s)	-0.35	-0.35	-0.33	-0.33	-0.33
CC5 – Positive following threshold (ft/s)	0.35	0.35	0.33	0.33	0.33
CC6 – Speed dependency of oscillation (1/(ft/s))	11.44	0	0	0	0
CC7 – Oscillation during acceleration (ft/s^2)	0.82	0.82	0.33	0.33	0.33
CC8 – Standstill acceleration (ft/s^2)	11.48	11.48	11.48	9.84	13.12
CC9 – Acceleration at 50 miles/hour (ft/s^2)	4.92	4.92	4.92	3.94	6.56

TABLE 2 Lane Change Parameters.

Parameter	Human-driven	Fehr & Peers	CoEXist normal	CoEXist cautious	CoEXist all-knowing
General behavior	Free selection	Free selection	Slow lane rule	Slow lane rule	Slow lane rule
Minimum headway (s)	0.5	0.37	0.5	0.5	0.5
Safety distance reduction factor	0.6	0.45	0.60	1	0.75
Maximum deceleration for cooperative braking (ft/s^2)	-3	-4	-3	-2.5	-6
Cooperative lane change	off	on	on	off	on

We evaluated five vehicle models' aggressive levels and ranked them from high to low in **Table 3**. The CoEXist all-knowing model was the most aggressive since it includes the shortest standstill distance, largest acceleration, and second shortest headway time. In contrast, the CoEXist cautious model is the least aggressive as it contains the largest headway time and safety distance reduction factor, as well as the lowest standstill acceleration. The Fehr & Peer model ranked second with the second lowest standstill distance and shortest headway time. This model is less aggressive than the CoEXist all-knowing model due to its larger car-following distance and reduced acceleration. The CoEXist normal model was very similar to the HDV model, but the CoEXist normal model ranked lower on aggressiveness due to the CoEXist normal model's cooperation during lane changes.

TABLE 3 Vehicle Models' Aggressive Levels Ranking from High to Low.

Aggressive rank	1	2	3	4	5
Vehicle model	CoEXist all-knowing	Fehr & Peers	Human-driven	CoEXist normal	CoEXist cautious

Case Studies

In the simulation, two traffic volume conditions represented moderate and rush-hour traffic. In the moderate traffic condition, 2500 vehicles per hour passed through the highway section in **Figure 1**. In this condition, 200 vehicles per hour entered the highway from the on-ramp at **c** and another 200 vehicles per hour exited the highway at **d**. For the high traffic condition, those numbers were 3500, 400, and 400 respectively. These low and high traffic volumes were estimated based on the maximal traffic capacity

(*42*). The four AV models were separately tested in the two traffic conditions, and the ratio of AVs to HDVs in the overall vehicle fleet varied (25%, 50%, 75%, and 100%). Two conditions with only HDVs were tested as the baseline with moderate and rush-hour traffic. The simulation took one hour to collect travel times and SSAM measures.

RESULTS

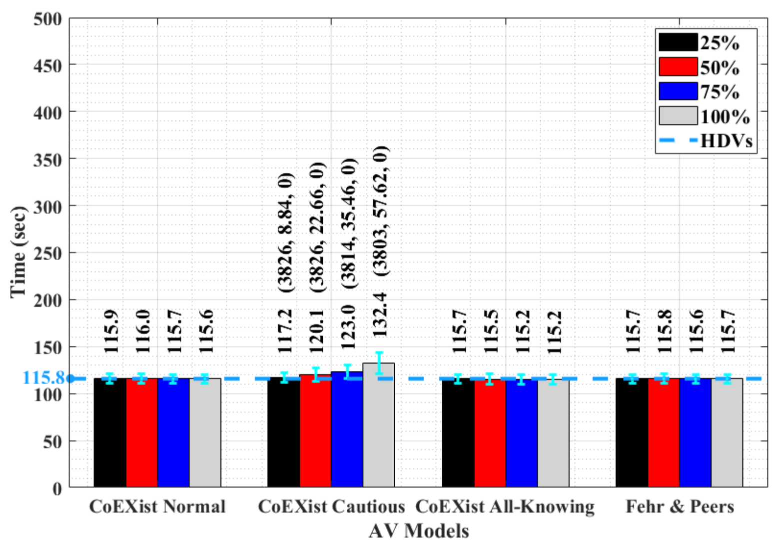
Traffic Efficiency

Travel Time through the Entire Highway Section

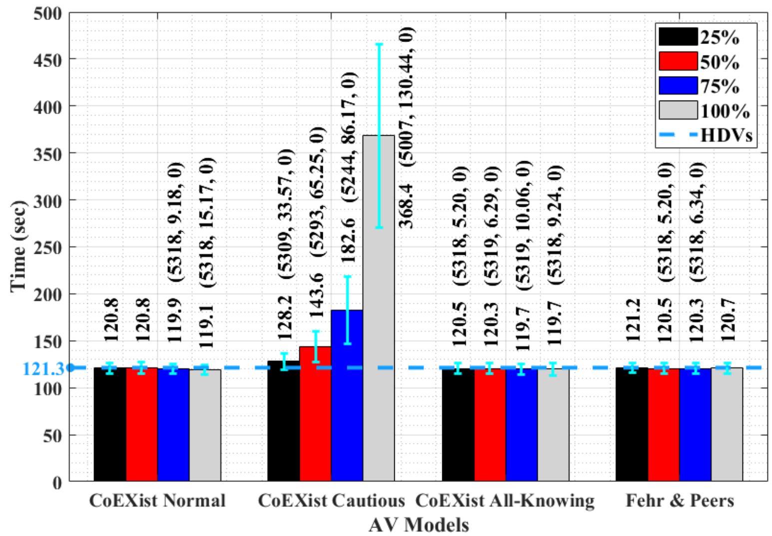
Figure 2 plots the average time and standard deviation for a vehicle to pass through the entire highway section in the moderate traffic condition (**Figure 2.a**) and rush-hour traffic condition (**Figure 2.b**). For example, if the AVs' behavior followed the CoExist normal behavior model and AVs comprised 25% of the overall vehicle fleet, each vehicle in that mixed fleet took an average of 115.9s to pass the entire highway section in the moderate traffic condition, but the same vehicle would need, on average, 120.8s to pass that same highway section in rush hour. The testing baseline was an entire vehicle fleet consisting of only HDVs. The average travel time was 115.8s plotted as a blue dashed line in **Figure 2**, with a standard deviation of 4.9s.

In the moderate traffic condition, the average travel time was slightly less than the baseline condition regardless of the AV ratios when the AVs behaved the CoEXist all-knowing model and the Fehr & Peers model. When the AVs followed the CoEXist normal model, the mixed fleet initially spent more time than the baseline condition but later became slightly better with a 75% or 100% AVs ratio. The average travel time was longer with CoEXist cautious AVs passing through the highway section, and there was a time increase when the AV ratio was higher. However, none of these differences were statistically significant using t-test comparisons with the HDV data. For a fleet of all CoEXist cautious AVs, the average travel time was 132.4s with a standard deviation of 11.6s. This fleet spent statistically more time than the baseline. The family-wise alpha value is 0.0000625 (0.001/16).

In the rush-hour traffic condition, the fleet with CoEXist cautious AVs spent statistically more time than the baseline. In contrast, the fleets of CoEXist all-knowing AVs were slightly but statistically faster than the HDV fleet. In addition, fleets with a large portion of CoEXist normal AVs were also faster than the than the HDV baseline.



(a)



(b)

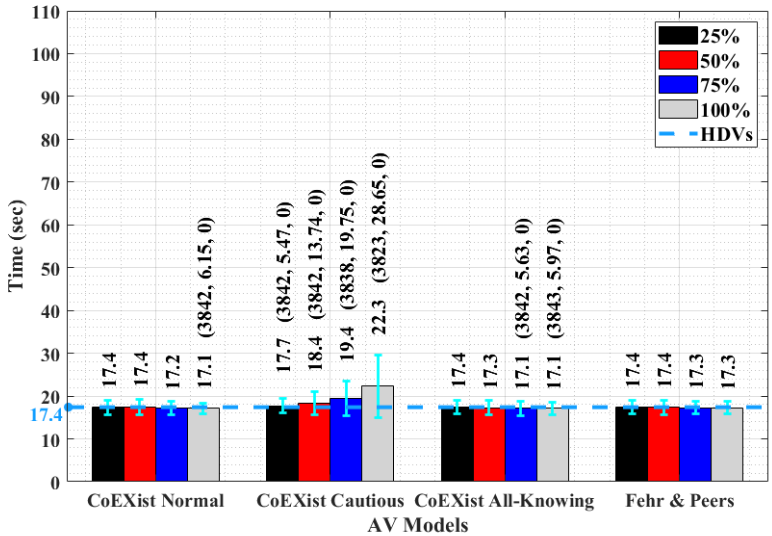
Figure 2 The average time that vehicles take to pass the entire highway section in the moderate traffic condition (a) and rush-hour traffic condition (b). Error bars represent one standard deviation. If the travel times are significantly different, t-test results are presented with (degrees of freedom, t ratios, and p-values.

Travel Time through the Segment from b to f

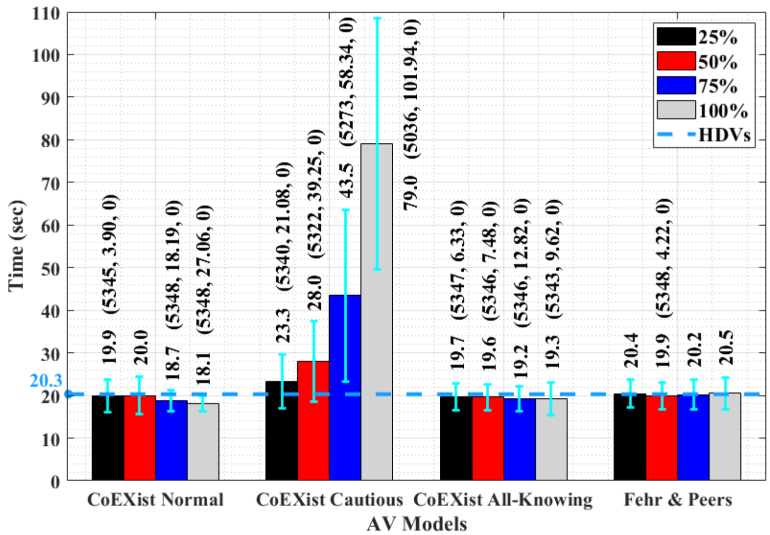
Figure 3 plots the average travel times and standard deviations through the segment from **b** to **f** in the moderate traffic condition (**Figure 3.a**) and rush-hour traffic condition (**Figure 3.b**). The travel times of mixed fleets with CoExist normal AVs, CoEXist all-knowing AVs, or Fehr & Peers AVs were close the HDV fleet (mean = 17.4s, standard deviation = 1.7s) to pass through that segment in the moderate traffic, when the AV rate was 25%. However, the mixed fleet with CoEXist normal and all-knowing vehicles was statistically faster than the HDV fleet when the mixture ratio was high. The fleet with CoEXist cautious AVs took more time than the HDVs, and travel time increased with more AVs in the fleet. This fleet spent statistically more time than the HDV baseline. This observation was consistent with the travel time passing through the entire highway section.

During rush hour, the mixed fleet with CoEXist cautious AVs still had the longest travel times, and these times increased with an increasing ratio of AVs. In contrast, fleets with CoEXist normal AVs and CoEXist all-knowing AVs were slightly but statistically faster than the HDV fleet (mean = 20.3s, standard deviation = 3.8s). The advantage of CoEXist normal AVs over HDVs became more apparent with more AVs in the fleet.

The travel times for segment **a** to **d** and **c** to **e** revealed similar distribution patterns, which were not included in this paper. The fleet with CoEXist cautious AVs was the slowest, and more time was needed with more AVs in the fleet. Fleets with CoEXist normal AVs or all-knowing AVs were slightly faster than the fleet with only HDVs regarding the travel time, but not outside one standard deviation.



(a)



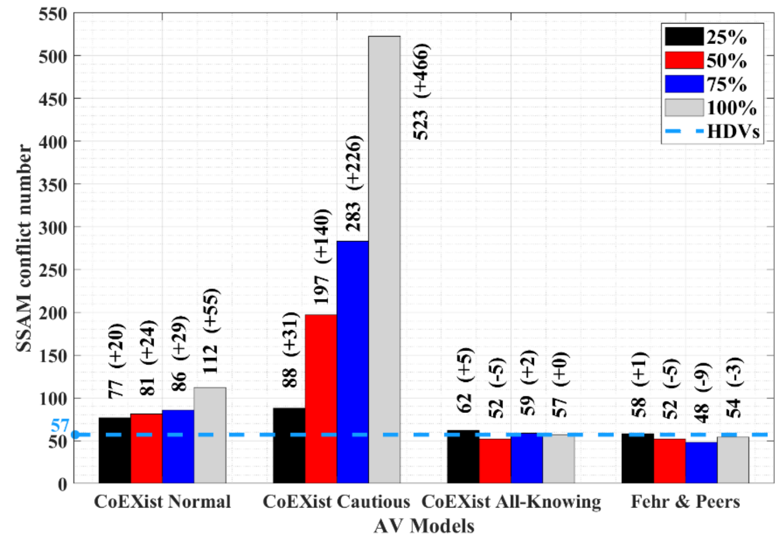
(b)

Figure 3 The average time that vehicles pass the segment from b to f in the moderate traffic condition (a) and rush-hour traffic condition (b). Error bars represent one standard deviation. If the travel times are significantly different, t-test results are presented with (degrees of freedom, t ratios, and p-values).

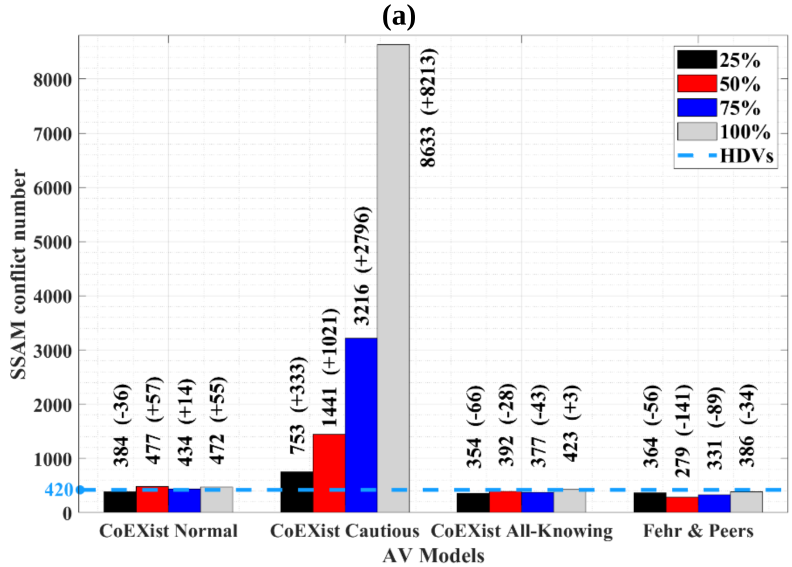
Traffic Safety

SSAM measures in the moderate traffic condition and rush-hour condition are shown in **Figure 4**. Similarly, the SSAM measure for an HDV fleet as a baseline was plotted as a dashed line at 57 conflicts for moderate and 420 for rush-hour traffic. The conflict differences between AV fleets and the HDV fleet are present in the brackets. In the moderate case, fleets with CoEXist normal AVs and CoEXist cautious AVs had more conflicts, and the conflict number increased with more AVs in the fleet. In contrast, the number of conflicts in the CoEXist all-knowing AVs and Fehr & Peers AVs models oscillated around the number of the HDV fleet.

During rush hour, the fleet with CoEXist cautious AVs had the most potential conflicts, which reached 8633 for a fully autonomous vehicle fleet. The conflict number of the other three types of fleets were similar to the HDV fleet. The conflict number was 384 when the fleet consisted of 25% CoEXist normal AVs, and this number increased to 472 when the fleet was fully AV. The conflict numbers of the fleets of CoEXist all-knowing AVs and Fehr & Peers AVs increased overall from 354 and 364 at 25% AVs to 423 and 386 with full AVs in the fleet. The lowest number of conflicts (279) occurred in the Fehr and Peers model at 50% AVs, but this result was not seen in any other model.



(a)



(b)

Figure 4 Plots of the traffic conflict number in the moderate traffic condition (a) and rush-hour traffic condition (b). The differences between the AV fleets with HDV fleet are presented in the brackets.

DISCUSSION

In our study, fleets of AVs did not demonstrate large` improvements for traffic efficiency and safety seen by in other research (*40*). The CoEXist cautious AVs were the least aggressive as they respected the rules of the road and theoretically adopted safe behaviors. However, their over-conservative driving behaviors potentially posed another set of risks to traffic. Fleets with CoEXist cautious AVs took the longest time to pass through a highway segment and had the highest number of traffic conflicts. When two overly cautious vehicles came close to each other during lane merging, for example, they attempted to mutually avoid the other car and wait for a safe situation. This process slowed traffic and increased potential conflicts. Interestingly, there have been a high number of rear-end collisions between actual AVs and human-driven cars in the real world (*43*), where the human drivers did not anticipate the AVs' overly cautious behaviors. These kinds of correlations add confidence to such traffic flow simulation models.

When the AVs were sufficiently capable and appropriately aggressive, such fleets could improve the traffic efficiency and safety, albeit somewhat small per previously-published simulation models. In addition, the improvements often became larger with a higher ratio of AVs, but results across various conditions were not consistent. This suggests the ability of AVs to improve traffic efficiency and safety is likely conditional, predicated upon many external factors including AV capabilities and driving styles. Thus, it is prudent to extend our current studies to other road networks and driving environments to thoroughly test how increasing fleet sizes of AVs influence traffic efficiency and safety. In addition, it is worth reviewing current AV models for their validity across many road types, which may shed light on which kinds of AVs could improve traffic efficiency and safety.

Limitations of the Current Study

Our current study was conducted within VISSIM using the default HDV model, AV models, and SSAM. Recalibrations of those HDV models with local traffic data and SSAM for AVs may be desirable for more generalizable results. The validity of the AV models needs to be further tested to see whether they satisfy expectations for AV performance. In addition, VISSIM does not have a vehicle crash detection function that runs in real-time, therefore SSAM was used to post-estimate crashes. SSAM has been criticized for its inability to accurately estimate lane changes (*44)*, which would be especially relevant for a mixture of HDVs and AVs in these settings. Other safety models should be used to further validate these estimates.

CONCLUSIONS

In this paper, we investigated how AVs could influence traffic efficiency and safety given varying AV aggressive driving behaviors. Two AV models with four variants developed by two research groups, one from Europe and another from California, were tested on a simulated highway section of Durham, NC, USA, along with a baseline model of human drivers. Four vehicle fleet travel times through four segments of a highway section were used to evaluate traffic efficiency, and SSAM estimates of vehicle conflicts were generated from post-simulation data of vehicle trajectories. The results show that overly conservative AVs are not more efficient and potentially pose new risks to traffic efficiency and safety. In addition, more aggressive AVs with nearly flawless systems appeared to provide small improvements over human-driven vehicles. Potential future work includes examining the effects of AVs in more complicated traffic scenarios that include responding to a wider variation of human behaviors as well as different reliabilities and capabilities of the AVs.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: S. Li, D. Seth, M. Cummings; data collection: D. Seth; analysis and interpretation of results: S. Li, D. Seth; draft manuscript preparation: S. Li, M. Cummings, D. Seth. All authors reviewed the results and approved the final version of the manuscript.

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