PROCEEDINGS OF SPIE

SPIEDigitalLibrary.org/conference-proceedings-of-spie

Evaluating the driving behavior of autonomous vehicles and human driver vehicles in mixed driver environments at a signalized intersection

Yang, Xinyi, Ahmad, Salman, Nelson, Martha, Rogers, Joshua, Ren, Yihao, et al.

Xinyi Yang, Salman Ahmad, Martha Nelson, Joshua Rogers, Yihao Ren, Ying Huang, Pan Lu, "Evaluating the driving behavior of autonomous vehicles and human driver vehicles in mixed driver environments at a signalized intersection," Proc. SPIE 12046, Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2022, 1204610 (18 April 2022); doi: 10.1117/12.2613057

Event: SPIE Smart Structures + Nondestructive Evaluation, 2022, Long Beach, California, United States

Evaluating the Driving Behavior of Autonomous Vehicles and Human Driver Vehicles in Mixed Driver Environments at A Signalized Intersection

Xinyi Yang[a], Salman Ahmad[a], Martha Nelson[b], Joshua Rogers[c], Yihao Ren[d], Ying Huang*[a], Pan Lu[d]
[a]Dept. of Civil and Environmental Engineering, North Dakota State University, Fargo, ND, USA 58108-6050; [b]Dept. of Mathematics, North High School, Fargo, ND, USA 58102; [c]Dept. of Science, Davies High School, Fargo, ND, USA 58104; [d]Dept. of Transportation, Logistics and Finance, North Dakota State University, Fargo, ND USA 58102

ABSTRACT

With the rapid development of smart cities, interest in vehicle automation continues growing. Autonomous vehicles are becoming more and more popular among people and are considered to be the future of ground transportation. Autonomous vehicles, either with adaptive cruise control (ACC) or cooperative adaptive cruise control (CACC), provide many possibilities for smart transportation in a smart city. However, traditional vehicles and autonomous vehicles will have to share the same road systems until autonomous vehicles fully penetrate the market over the next few decades, which leads to conflicts because of the inconsistency of human drivers. In this paper, the performance of autonomous vehicles with ACC/CACC and traditional vehicles in mixed driver environments at a signalized intersection were evaluated using the micro-simulator VISSIM. In the simulation, the vehicles controlled by the ACC/CACC and Wiedemann 99 (W99) model represent the behavior of autonomous vehicles and human driver vehicles, respectively. For these two different driver environments, four different transport modes were comprehensively investigated: full light duty cars, full trucks, full motorcycles, and mixed conditions. In addition, ten different seed numbers were applied to each model to avoid coincidence. To evaluate the driving behavior of the human drivers and autonomous vehicles, this paper will compare the total number of stops, average velocity, and vehicle delay of each model at the signalized traffic intersection based on a real road intersection in Minnesota.

Keywords: Autonomous vehicles, mixed driver environments, signalized intersection

1. INTRODUCTION

The Bureau of Transportation Statistics, a part of the United States Department of Transportation, reported that the number of registered vehicles increased from 73,857,768 in 1960 to 275,924,442 in 2020 [1]. The light duty vehicles, trucks, and motorcycles account for around 94%, 4%, and 2% of the total vehicles, where the proportion of trucks and motorcycles increased from 1994 to 2020 [1]. Based on the report by the Office of Economic and Strategic Analysis of the United States Department of Transportation, congestion on the urban road network causes around 85 billion dollars per year that equivalent to 763 dollars per commuter annually [2]. Therefore, it is important to reduce traffic congestion. Autonomous vehicles (AVs) that are the future of ground transportation provide the possibilities.

However, full adoption of autonomous vehicles will take a few decades. Before that, conventional and autonomous vehicles need to share the road systems. This paper simulates the traditional and autonomous vehicles driving in mixed driver environments at a signalized intersection. The organization of the remainder of the paper is as follows: Section II describes the models that control the traditional and autonomous vehicles, and the model set up with a micro-simulator; Section III evaluates the models using the micro simulator VISSM and discuss the simulation results; Sections IV concludes the work and suggest future applications.

2. METHODOLOGIES

2.1 ACC/CACC models

The car-following models, such as stimulus-response models, safe-distance models, desired headway models [3-5], were developed to control the AVs. Adaptive cruise control (ACC) car-following model [6] is one of the most adopted stimulus-

Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2022, edited by Daniele Zonta, Branko Glisic, Zhongqing Su, Proc. of SPIE Vol. 12046, 1204610 · © 2022 SPIE · 0277-786X · doi: 10.1117/12.2613057

response models, it is able to adjust speed through the information from preceding vehicle automatically [7, 8]. The acceleration range of the AVs control with ACC systems can be estimated by [6, 8, 10]:

$$a = max[a_{min,} min(a_{c,} a_{max})], \quad (1)$$

where, a_{min} and a_{max} are the minimum and maximum allowed acceleration. a_c is the control acceleration, which can be calculated as:

$$a_c = k_a * a_p + k_v * (v_p - v) + k_d * (r - r_{system}), \quad (2)$$

where, a_p is the acceleration of preceding vehicle, v and v_p are the speed of the ego and preceding vehicle. k_a, k_v and k_d are constant factors, r is the following distance between the ego and preceding vehicle, r_{system} is recommended following distance according to the minimum desired time gap of the AV (t_{system}).

$$r_{system} = t_{system} * v \quad (3)$$

To improve the safety of the AVs, cooperative adaptive cruise control (CACC) was developed [11]. The CACC model is the same as the ACC model but the CACC system is able to make the decision with the data from multiple vehicles around the AVs and follow the previous vehicle at shorter headway. Therefore, k_a of the CACC model is 1 while its value of the ACC model is 0. In addition, the minimum desired time gap of the CACC model is decreased from 1.4 seconds of ACC to 0.5 seconds.

2.2 Simulation model set up

To evaluate the driving behaviours of traditional and autonomous vehicles, this study conducted a case study using a micro-simulator, VISSIM. VISSIM has a default car-following model, Wiedemann 99 (W99), that simulates the driving behavior of human drivers. Different from the internal model W99, which is able to use directly, the dynamic link library needs to be revised with C++ in order to implement ACC/CACC model in VISSIM. The test was performed on a simulated signalized intersection based on the real road intersection in Minnesota with the vehicle's input numbers (unit is a number of vehicles per hour per lane (pc/h/ln)) as shown in Figure 1.

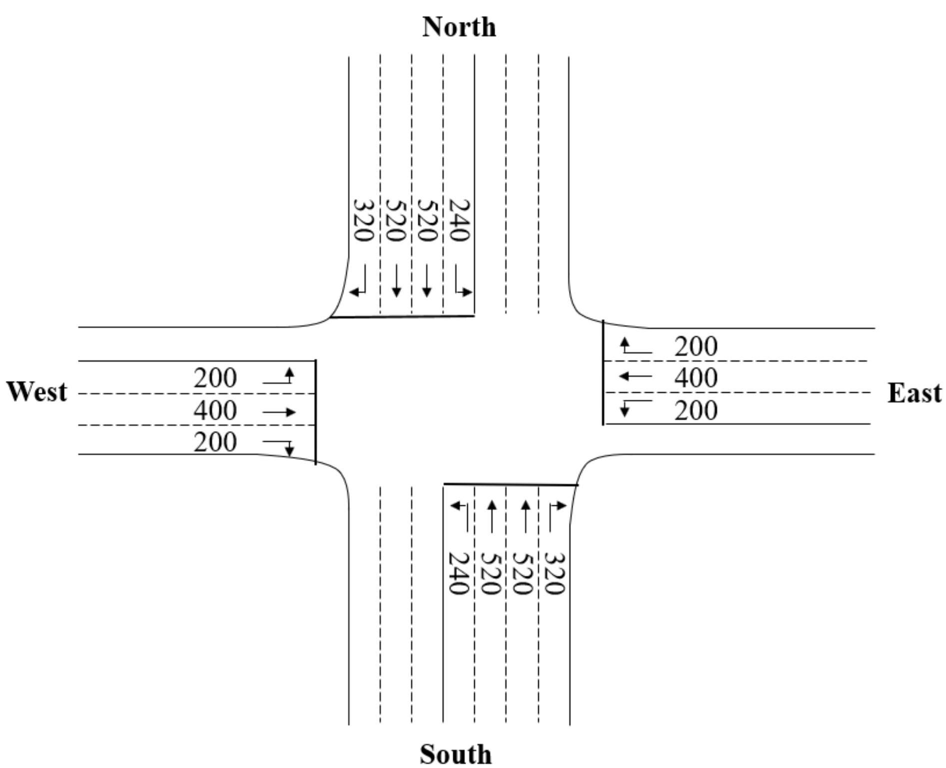

Figure 1. Two phases signalized intersection

The vehicles controlled by the ACC/CACC and W99 model represent the behavior of autonomous vehicles and human driver vehicles, respectively. Considering the conditions of real-world transportation, the three most common driving models light duty vehicles, trucks, and motorcycles were investigated. The simulation worked as shown in figure 2, where the blue and green vehicles controlled by ACC/CACC and W99 models.

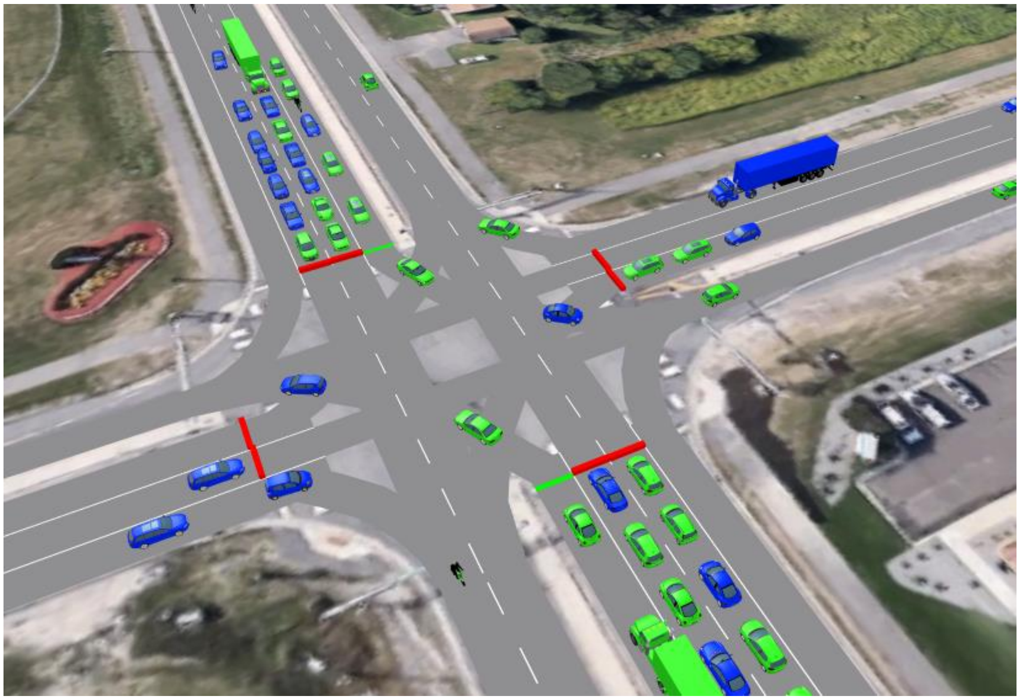

Figure 2. Diagram of vehicle information when simulated in the VISSIM (Source: VISSIM)

There are ten different seed numbers, which represent ten different conditions that were applied to each model and mode to avoid coincidence. The default velocity was set as 13.89 m/s (50 km/hr). For each simulation run, the total simulation time was set to be 4,500 seconds, where each travel interval was 900 seconds, with the first 900 seconds was removed in the traffic simulation results since it allocated for simulation warmup. The simulation parameters as shown in Table 1.

Table 1. Parameters of the Simulations.

Parameters	
Time Interval	0 – 900 (warmup time, not included)
	900-1800
	1800-2700
	2700-3600
	3600-4500
Default Velocity	22.35 m/s
Model	ACC
	CACC
	W99
Conditions	10

3. SIMULATION RESULTS

Light duty vehicles, trucks, and motorcycles are the three main transportation modes. Figure 3 (a-f) demonstrates average delay, average velocity, and number of stops of the light duty vehicles controlled by the W99, ACC, and CACC models. The average delay decreased when the percentage of the vehicle controlled by ACC and CACC models increased, and the average velocity is shown in the opposite way. The number of stops increased with the percentage of vehicles controlled by ACC model and decrease with CACC model. The vehicle controlled by the ACC model has a less average delay and higher average velocity, however, the vehicle controlled by the CACC model generates fewer stops, which decreases the fuel consumption.

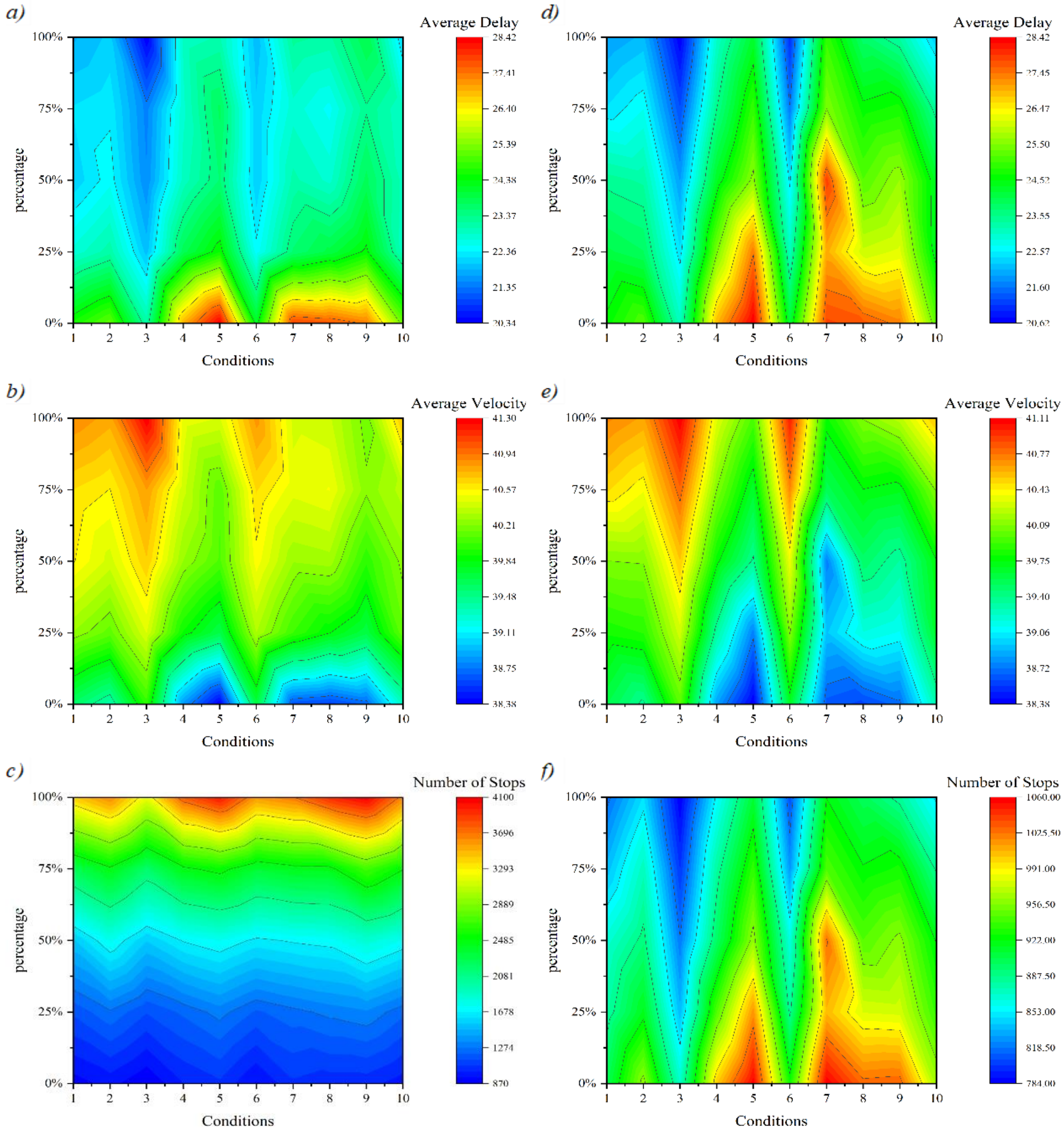

Figure 3. (a) average delay, (b) average velocity, (c) number of stops of the light duty vehicles control by W99 and ACC model; and (d) average delay, (e) average velocity, (f) number of stops of the light duty vehicles control byW99 and CACC model.

Considering full trucks and motorcycles are extreme conditions since their size is relatively bigger and smaller than the normal vehicles, the difference between the trucks and motorcycles controlled by ACC and CACC model is not obvious. Therefore, this study only shows average delay, average velocity, and number of stops of the trucks and motorcycles controlled by W99 and ACC model (in Figure 4 (a-f)). Based on the results from Figure 4, the trend of the average delay, average velocity, and the number of stops is the same as the full light duty vehicle conditions, but the average velocity of trucks are lower than light duty vehicles while the average delay and number of stops are higher. The result of the motorcycles compared to the light duty vehicles are the exact opposite.

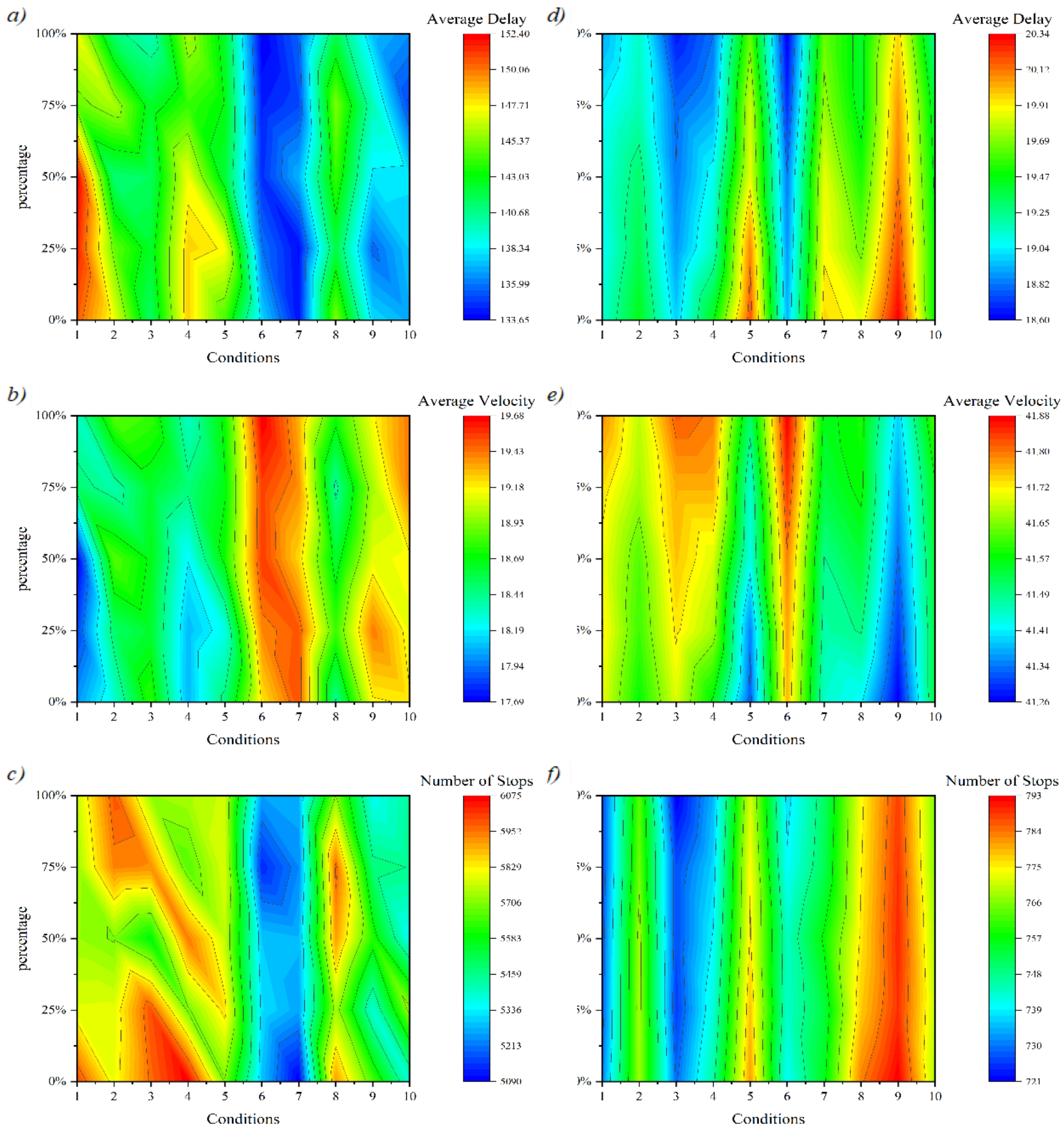

Figure 4. (a) average delay, (b) average velocity, (c) number of stops of the trucks control by W99 and ACC model; and (d) average delay, (e) average velocity, (f) number of stops of the motorcycles control byW99 and ACC model

In 2020, there are light duty vehicles, trucks, motorcycles, and other vehicles that constitute 91.74%, 4.89%, 3.01%, and 0.36% of total vehicles [1]. This study is not included the other vehicles, therefore the percentage of the light duty vehicles, trucks, and motorcycles would be 92.07, 4.90, and 3.03 of the total vehicles in this study. When the penetration of the autonomous vehicles is 0%, 25%, 50%, 75%, and 100%, the percentage of each mode is shown in table 2. The average delay, average velocity, and number of stops of the mix transportation mode conditions are shown in Figure 5 (a-f) that shows the same trend as full light duty vehicles.

Table 2. Percentages of the transportation modes inputs to the simulation in different autonomous vehicle penetration.

Penetration / Modes	0%	25%	50%	75%	100%
light duty vehicle	0.00%	23.02%	46.04%	69.05%	92.07%
truck	0.00%	1.23%	2.45%	3.68%	4.90%
motorcycle	0.00%	0.76%	1.51%	2.27%	3.03%

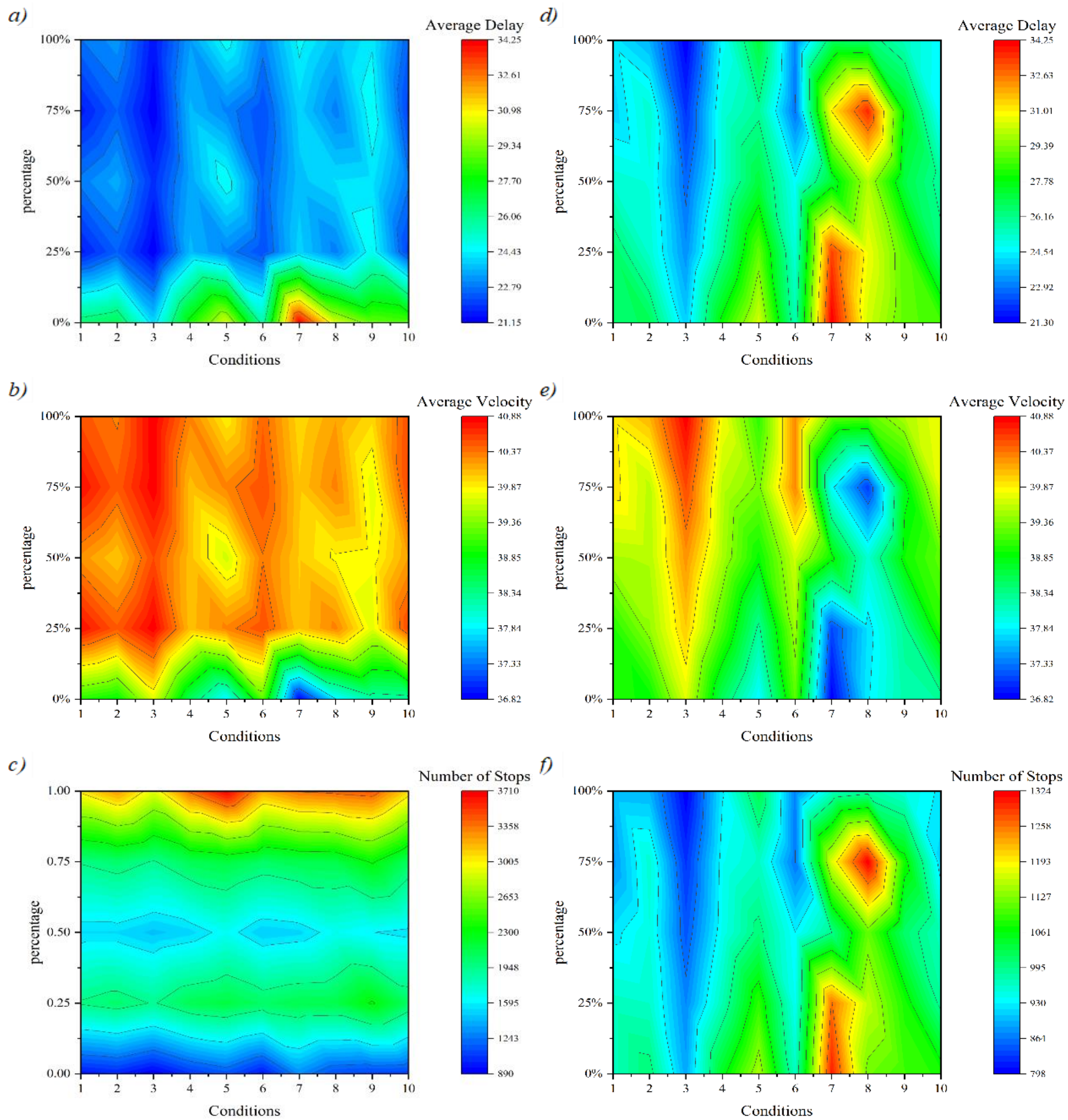

Figure 5. (a) average delay, (b) average velocity, (c) number of stops of the mix vehicles control by W99 and ACC model; and (d) average delay, (e) average velocity, (f) number of stops of the mix vehicles control byW99 and CACC model

Figure 6 shows the trend of average velocity and number of stops of the vehicles (light duty vehicles, motorcycles, and trucks) controlled by the ACC model. When the penetration rate increases from 0 to 1, the number of stops and average velocity increase. The higher average velocity eases the transportation congestion but the relatively high number of stops influences the environment.

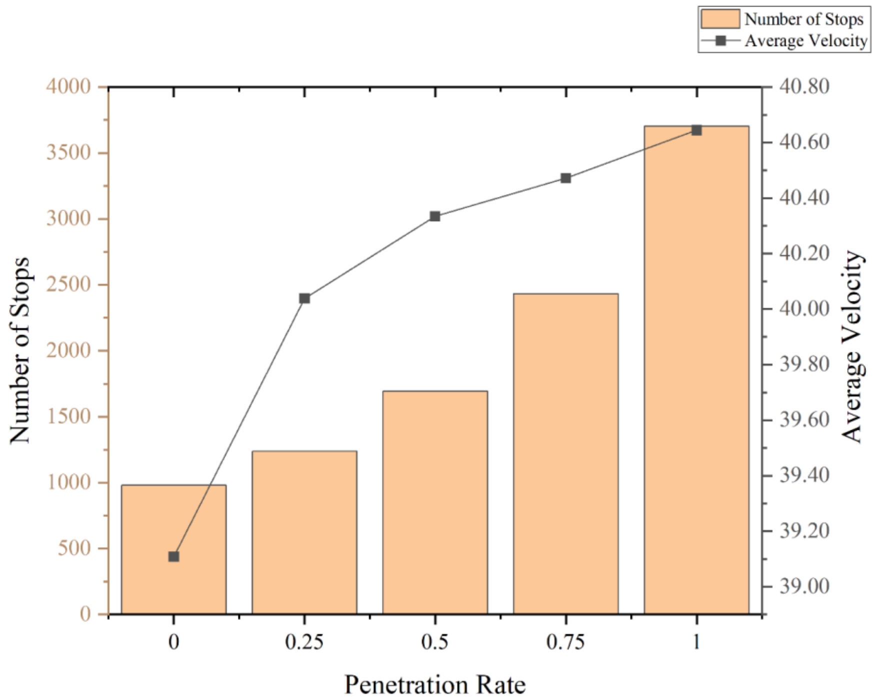

Figure 6. The trend of average velocity and number of stops with different penetration rate of various vehicles control by the W99 and ACC model.

4. CONCLUSION AND FUTURE WORK

This paper demonstrates how autonomous vehicles ease traffic congestions when the vehicle modes are light duty vehicles, trucks, and motorcycles. The simulation test was performed on a micro-simulator, VISSIM. The vehicles controlled by ACC/CACC models and W99 models simulate the autonomous and conventional vehicles at a signalized intersection. The penetration of the autonomous vehicles from 0%, 25%, 50%, and 100% are tested, there are 10 traffic scenarios are applied to each condition to make a realistic demonstration of traffic simulation. Results demonstrate there is the same trend among all four kinds of traffic modes: the average velocity and number of stops increased when the percentage of the vehicle controlled by ACC or CACC models is increasing, while the average delay decreased. The vehicles controlled by the ACC model generate less average delay and higher average velocity while the vehicles controlled by the CACC model generate fewer stops, which decreases the fuel consumption. In the future, there are more research will be focused on building a model that improves the ACC and CACC model to control the vehicles in the most optimal modes, which drive quickly and make fewer stops.

ACKNOWLEDGMENT

The authors express their gratitude to the funding provided to support this study from the Mountain-Plains Consortium (MPC), a university transportation center funded by the U.S. Department of Transportation.

REFERENCES

[1] Bureau of Transportation Statistics, “Number of U.S. aircraft, vehicles, vessels, and other conveyances.” https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances (2020).
[2] U. S. DOT, "Assessing the Full Costs of Congestion on Surface Transportation Systems and Reducing Them through Pricing." United States Department of Transportation,

https://www.transportation.gov/sites/dot.dev/files/docs/Costs%20of%20Surface%20Transportation%20Congestion.pdf (2009).

[3] Aghabayk K., Sarvi M., and Young W., "A state-of-the-art review of car-following models with particular considerations of heavy vehicles," *Transport reviews*, vol. 35, no. 1, pp. 82-105 (2015).

[4] Brackstone M., and McDonald M., "Car-following: a historical review," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 2, no. 4, pp. 181-196 (1999).

[5] Chen J., Liu R., Ngoduy D., and Shi Z., "A new multi-anticipative car-following model with consideration of the desired following distance," *Nonlinear Dynamics*, vol. 85, no. 4, pp. 2705-2717, (2016).

[6] VanderWerf J., Shladover S., Kourjanskaia N., Miller M., and Krishnan H., "Modeling effects of driver control assistance systems on traffic," *Transportation Research Record*, vol. 1748, no. 1, pp. 167-174 (2001).

[7] Li S., Li K., Rajamani R., and Wang J., "Model predictive multi-objective vehicular adaptive cruise control," *IEEE Transactions on Control Systems Technology*, vol. 19, no. 3, pp. 556-566 (2011).

[8] Wang D. and Jin S., "Review and outlook of modeling of car following behavior," *China Journal of Highway and Transportation*, vol. 25, no. 1, pp. 115-127 (2012).

[9] VanArem B., Van Driel C. J., and Visser R., "The impact of cooperative adaptive cruise control on traffic-flow characteristics," *IEEE Transactions on intelligent transportation systems*, vol. 7, no. 4, pp. 429-436 (2006).

[10] Zhao L., and Sun J., "Simulation framework for vehicle platooning and car-following behaviors under connected-vehicle environment," *Procedia-Social and Behavioral Sciences*, vol. 96, pp. 914-924 (2013).

[11] Milanés V., Shladover S. E., Spring J., Nowakowski C., Kawazoe H., and Nakamura M., "Cooperative adaptive cruise control in real traffic situations," *IEEE Transactions on intelligent transportation systems*, vol. 15, no. 1, pp. 296-305 (2013).