Quantifying Impacts of Connected and Autonomous Vehicles on Traffic Operation using Micro-simulation in Dubai, UAE

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Abstract: Connected and Autonomous Vehicles (CAVs) will change the transportation system we know with their substantial impacts on the level of safety, traffic operation, fuel consumption, air emissions among other aspects. A large segment of the general public and decision makers are still sceptical of CAVs' benefits and impacts. This study aims at quantifying the impacts of CAVs on traffic operation using micro-simulation of a 7-kilometer-freeway segment in Dubai, UAE. The simulation was run for different market penetration rates (MPRs) ranging from 0% (no CAVs) up to 100% (all CAVs), in 10% increment. Additionally, multiple scenarios under different traffic volumes were also modelled utilizing PTV VISSIM. To quantify the impacts of CAVs, three performance measures were collected, namely the average delay, average speed, and total travel time. The results showed that the highest impact of CAVs occurs in terms of delay, with a decreased average delay of up to 86%. The other performance measures also show improvement, with 42% speed increase and 25% travel time reduction. Moreover, CAVs show more significant changes at lower traffic volume conditions (off-peak hour).

1 INTRODUCTION

As transportation engineering touches all kinds of people and affects their everyday life, it requires an extensive amount of research backing up the ever-continuing development of this field. Both researchers and engineers working in traffic-related domains often get the opportunity to experience their work first-hand and its implications for drivers, commuters, or even pedestrians. Among the developments that are coming relatively soon to our roads are Connected and Autonomous Vehicles (CAVs). The possible changes and impacts these vehicles will have on people's commute experiences are countless.

Due to their significance and vital role in the lives of the public, CAV impacts are expected to reach numerous aspects. Some impacts will be directly related to CAV technologies and applications like safety, energy, and fuel consumption, while other impacts will be a result of the side effects of the new technology, like land use, public resilience, and other social effects.

An essential element to study in the case of connected vehicles is the transition period that will span for a significant period of our future. In the transition period, roads and networks will have to accommodate both connected and conventional vehicles with varying market shares. CAVs and conventional vehicle interactions may lead to some undesirable effects on their operation, limiting the benefits of CAVs and even possibly affecting the planners and decision-makers' attitude towards accepting CAVs.

Some commercial cars with autonomous features already roam our streets and have been doing so since 1977 (Bertini et al., 2016) when first automated cars followed a track of white striped lines on the road at speeds of 20 mph. It is widely expected that CAVs will be available on the mass market by 2022 to 2025 (Ye and Yamamoto, 2017).

The field of Intelligent Transportation Systems (ITS) has become more popular in recent years. ITS provide various users with real time information to

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make safer and more intelligent decisions when using the transport networks. They also implement innovative services that are used in different modes of transport management. In general, ITS have the potential to improve safety, productivity, and mobility of transportation performance which could be achieved by traffic planners (Z. Yang and Pun-Cheng, 2017).

Road vehicles have gradually become technologically more advanced throughout the past decades with a focus on advancing traffic operation conditions vehicle safety and comfort. Although vehicle automation has been on the horizon for just as long, it is only since the turn of the century that it has started to find its way into production vehicles (Calvert et al., 2017).

With various levels of autonomous vehicle technology from driver assist all the way to fully automated driverless vehicles, the terminology used to describe the automation applications must be clear. For this purpose, the Society of Automotive Engineers (SAE) sets out the taxonomy used when discussing the levels of automation in their international standard J3016 (Bradburn et al., 2017).

The findings will provide a comprehensive understanding of road networks in the near future. They will also serve as a strong basis for the vital decisions that will be made to ensure the safest and most beneficial methods of managing roads with CAVs. Moreover, this study will cover a wide range of CAV Market Penetration Rates (MPRs).

2 LITERATURE REVIEW

The literature provides different case studies and simulation environments to analyze the impacts of CAVs on traffic operation as well as other factors. As the topic is relatively interesting to many researchers, the amount of research into the topic is somewhat extensive.

2.1 Traffic Operation Impacts

Research that studied the impacts on traffic operations considered many performance measures. Among these, Guler et al. (2014) studied the delay as a performance measure and found that the increase in MPR from 0% up to 60% has a significant impact on reducing the average delay. This decrease in low demand scenarios reaches up to 60%. After an MPR of 60%, the rate of reduction decreases and the value of information from connectivity technologies diminishes (Ilgin Guler et al., 2014).

Shi and Prevedouros (2016) considered the effect on Level of Service (LOS) and their findings suggested that on a basic freeway segment the autonomous vehicles improve LOS from D to C when the MPR reaches 7%. The same case study shows that the connected vehicles improve LOS from D to C when the MPR reaches 3% (Shi and Prevedouros, 2016).

Moreover, the capacity difference was analyzed by Ye and Yamamoto (2017) who found that the capacity of the road increases as the CAV market penetration rate increases in a shared road. However, this increase is split between two phases, at MPRs lower than 30%, the road capacity increases slightly. After 30% MPR, the in-crease in capacity is largely determined by the level of automation, with higher levels of automation achieving higher capacity increase (Ye and Yamamoto, 2017).

2.2 Other CAV Impacts

Different studies considered the impacts on different aspects including the safety impact which was considered by Yang et al. (2017) who discovered that when the MPR reaches 25%, the risk of secondary crashes can be reduced by up to 33% under high-volume conditions. Additionally, if the traffic volumes are high, risk of secondary crashes can be reduced by about 10% at low MPR levels of around 5%. However, the benefit of CAVs would not be notable under low-volume conditions (H. Yang et al., 2017).

When considering the effect on greenhouse gas emissions, Wadud et al. (2016) suggested that automation might plausibly reduce road transport GHG emissions and energy use by nearly half depending on which effects come to dominate. In addition, many potentials for energy reduction benefits may be realized first under partial automation, while the major energy downside risks appear more likely at full automation (Wadud et al., 2016).

The impacts of CAV technologies even reach land use as Zhang et al. (2015) concluded the possibility to eliminate 90% of parking demand for clients who adopt the new systems, at a low MPR of 2%. Also, different Shared Autonomous Vehicle (SAV) operation strategies and client's preferences may lead to different spatial distribution of urban parking demand (Zhang et al., 2015)

Figure 1: Study area.

3 METHODOLOGY

Towards achieving our objective, the following three main steps were undertaken: (1) build the roadway geometry and calibrate CAV modelling, (2) prepare and test simulation scenarios; and (3) analyze traffic operation parameters.

To quantify the impacts of CAVs, the most widely used approach is micro-simulation, which provides a commonly acceptable prediction tool that helps in understanding the behavior of both CAVs and conventional vehicles on roadway networks once they become reality. Micro-simulation also reveals all the possible outcomes of proposed scenarios and approaches to implement the new technologies. The latest version of PTV VISSIM (version 11) was utilized to develop and run the simulations. This state-of-the-art software provides the most advanced virtual test bed to carry out and test the objectives of this study.

3.1 Study Area

The chosen freeway segment shown in Figure 1 of Sheikh Mohammad Bin Zayed road (E311) spans seven kilometers of five lanes in each direction. This roadway segment connects the two cities of Dubai and Sharjah and experiences high traffic demand compared to other freeways. It has three interchanges of the following types: clover-leaf, fully directional, and semi directional ramp with loops.

The geometry of the freeway segment was modeled in PTV VISSIM spanning seven kilometers shown in Figure 2 The model has reduced speed areas at ramps and loops of the interchanges to reflect human driving behaviour.

3.2 Model Development and Calibration

For the purpose of this study, two levels of calibration had to be followed: (1) calibrate the driver behaviour to reflect local freeway conditions. (2) calibrate the predicted behaviour of CAVs to ensure realistic forecasting of their impacts.

Three sub-models control the simulation process of the driver behavior in VISSIM: car-following model, lane changing model, and lateral behavior within a lane. The parameters of these model were modified as well as conflict resolution behaviour.

The simulation results were compared with field measurements to determine how close the simulation model emulates field conditions. Two validation measures of effectiveness were collected, namely the delay and Level of Service (LOS) measurements and two input values were finely tuned to reach accurate performance of the model namely, the standstill distance (CC0) and the headway (CC1).

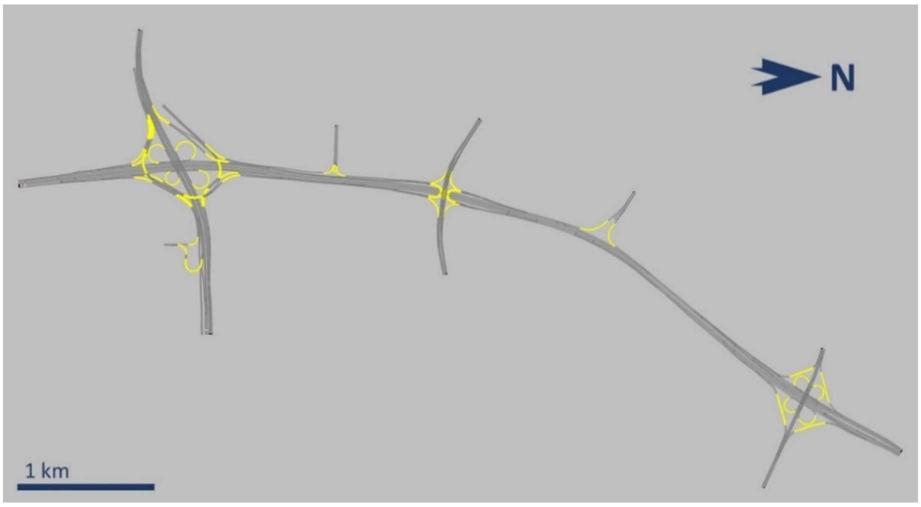

Figure 2: Freeway segment model in PTV VISSIM.

We used additional attributes in the driving behavior dialog of PTV VISSIM to model the predicted performance of CAVs. The car following model in VISSIM is based on the continued research of Wiedemann. In the 2018 version of PTV VISSIM, the Wiedemann 99 model is utilized and it consists of ten calibration parameters that have been modified to reflect CAV behavior.

In addition, a few other parameters were activated which do not fall under the car following main parameters:

- Enforced absolute braking distance was activated (a.k.a. brick wall distance), meaning vehicles using this driving behavior will always make sure that they could brake without a collision, if the leading vehicle comes to an immediate stop (turns into a brick wall). This condition applies also to lane changes (for the vehicle itself on the new lane and for the trailing vehicle on the new lane) and to conflict areas (for the following vehicle on the major road).
- The attribute to use implicit stochastics was disabled; a vehicle using this driving behavior does not use any internal stochastic variation that is meant to model the imperfection of human drivers.
- For all distributions which cannot be explicitly set by the user, a median value was used instead of a random value within a range to reflect consistency of CAV behaviour as opposed to human drivers. This affects the safety distance, the desired acceleration, and uncertainty for braking decisions.

3.3 Considerations and Assumptions

After calibrating the input values (mentioned in section 3.2), the following assumptions of speed and geometry were made:

- 5-lanes per direction for the main freeway segment with operational speed of 120 km/h and lane width of 3.6 m;
- 2-lanes per direction for the crossing arterial roads with operational speed of 100 km/h and lane width of 3.6 m;
- 2-lanes for the directional and semi-directional left ramps with operational speed of 60 km/h and lane width of 3.6m; and
- 1-lane for the loops and right ramps with lane width of 3.6 m and speed of 40 km/h and 60 km/h, respectively.
- Vehicle composition consists of 90% light vehicles and 10% heavy vehicles.

For all other not mentioned parameters, we used PTV VISSIM's default values.

3.4 Scenario Formulation

Road users will not switch to CAVs all of a sudden, instead they will start using them gradually as CAVs become more desirable and reliable, and as the standards and regulations become solid worldwide. The period between first introduction of CAVs and the time they become the main mode of transportation is called the transition period in which traffic will be a combination of conventional vehicles and CAVs, passing through different market shares of CAVs of market penetration rates (MPRs). For that reason, we need to study the behavior and traffic flow during each MPR. Some studies analyze low MPRs (0-25%) because they investigate the early adoption conditions (H. Yang et al., 2017), others use a wider range (0-75%) (Z. Chen et al., 2016). The rest of the literature in the field of CAV simulation use the full range of MPR (0-100%) but with different increments depending on their focus (Y. Chen et al., 2017; Talebpour & Mahmassani, 2016; K. Yang et al., 2016; Ye & Yamamoto, 2017).

In this study, we chose to cover the full range of MPR from 0% to 100% CAVs with 10% increment. This range was used to analyze traffic operation at every stage. After calibrating the model, the eleven scenarios of MPR were formulated.

Table 1: Traffic volume combinations.

Scenario ID	Major Road LOS	Minor Road LOS
1. BB	LOS B	LOS B
2. BD	LOS B	LOS D
3. BE	LOS B	LOS E
4. DB	LOS D	LOS B
5. DD	LOS D	LOS D
6. DE	LOS D	LOS E
7. EB	LOS E	LOS B
8. ED	LOS E	LOS D
9. EE	LOS E	LOS E

Furthermore, for each one of the MPR scenarios different traffic volume conditions were studied. The traffic volume effect was analyzed using traffic condition combinations between the major freeway and the minor intersecting roads. Based on three LOS conditions: B, D, and E, the volume per lane was determined, and then multiplied by the number of lanes for each road. The following nine combinations of LOS listed in Table 1 were used.

For each scenario multiple runs were used with different seed numbers to eliminate randomness of the model.

The total number of scenarios and number of required runs for each one was determined as follows:

Scenarios = 11 MPRs × 9 volume combinations

Scenarios = 99 scenario

Runs = 99 scenarios × 5 runs per scenario

Runs = 495 simulation runs

To extract the results, the average of the middle three runs was considered for each scenario.

4 RESULTS AND DISCUSSION

The results of our analysis are summarized in three performance measures: average delay, average speed, and total travel time. The results for each measure under the nine scenarios (from Table 1) are summarized in a single chart which shows the MPR on the x-axis and the percent change (increase or reduction) in the performance measure computed relative to the 0% MPR level.

4.1 Average Delay Results

Figure 3 shows the results of the average delay for all scenarios. It shows that the reduction in average delay is substantial reaching up to 86% in the best case with LOS B on both major and minor roads and 100% MPR. In all traffic volume combinations, the highest reductions in delay happen during initial stages of

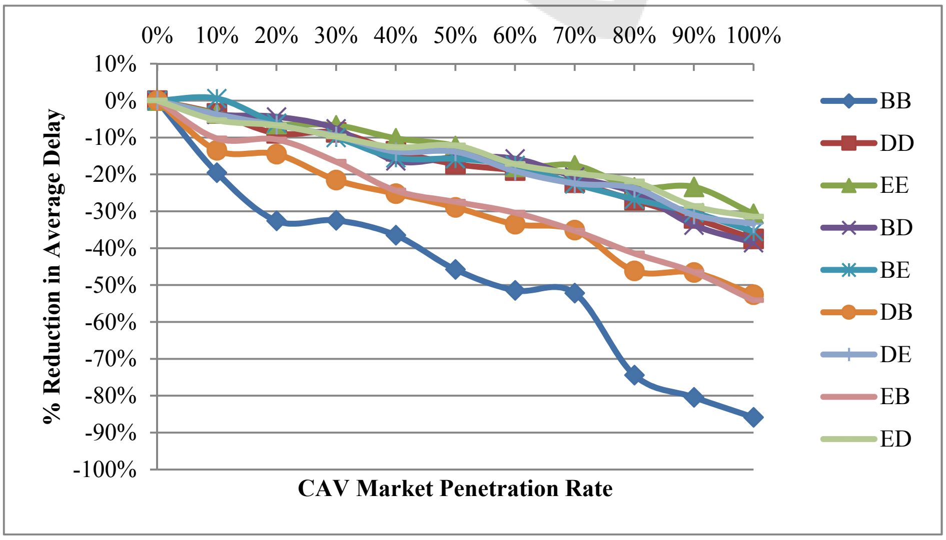

Figure 3: Average delay results.

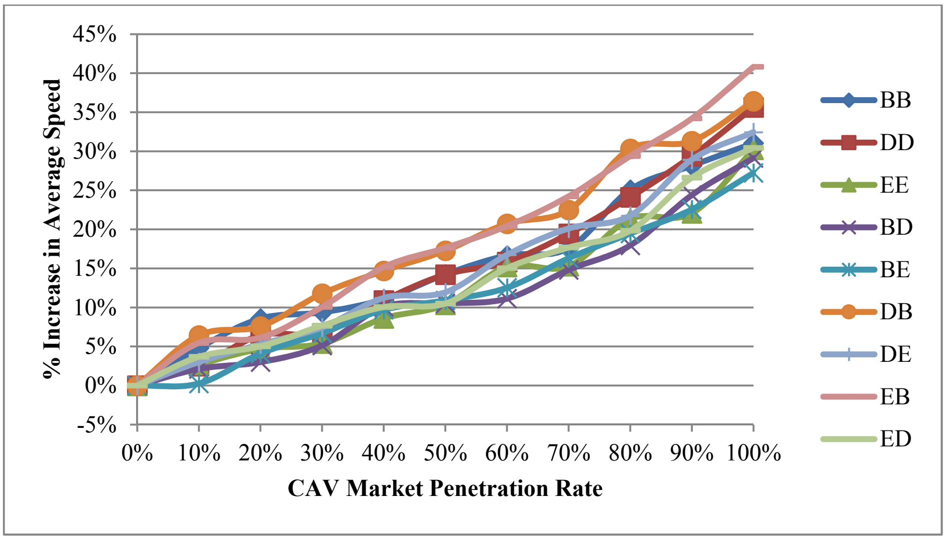

Figure 4: Average speed results.

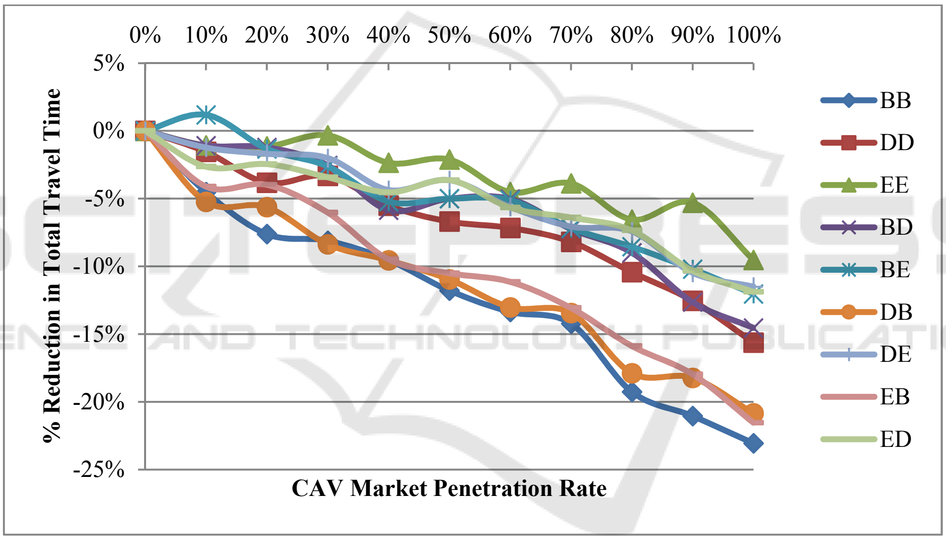

Figure 5: Total travel time results.

CAV utilization (0% to 20% CAVs) and right before full automation (70% to 80% CAVs). The bulk of the transition period between 20% and 70% has lower effects on average delays with a total of 17% reduction in the best-case scenario.

It's also clear that the benefits of CAVs are magnified in low traffic flow conditions (off-peak hour); this is apparent with the biggest reductions in delay happening at LOS B on the minor road and especially in the case of highest LOS on both major and minor roads.

4.2 Average Speed Results

Figure 4 shows the results of the average speed which follow a clear trend of increase ranging from 25% to 40%. The highest impact reaches over 40% increase in average speed with 100% MPR and LOS E on major road and B on minor road. The overall trend is clear, showing a steady rise in speed with the automation takeover. The results of different traffic volumes are somewhat similar; meaning that speed increases in all conditions (peak hour and off-peak hour).

The difference between the results of the two performance measures: average delay and average speed show that the delay is highly affected by the traffic volume variation. Average delay results show a huge decrease at higher MPRs under low traffic volume conditions. This observation is not apparent in average speed results, where the difference is not affected by different volume scenarios (except for a slight variation).

4.3 Total Travel Time Results

Figure 5 shows the results of the total travel time. The overall trend is a clear reduction in travel time with the increase of CAV shares ranging from 10% to 24%. Moreover, the graph shows big variations between different traffic flow conditions in terms of total travel time. The benefit gets to almost 24% reduction in total travel time for LOS B on both major and minor roads at 100% MPR, this enforces the outcome that CAV benefits become more significant at low traffic volumes.

At high traffic volumes (LOS E on major road and LOS E on minor road), the reduction in travel time becomes turbulent. Although the overall trend is a reduction of 10% in travel time, the results at lower MPRs show sometimes a slight increase; this could be a result of oversaturation of the network which causes long queues filling the whole segment.

5 CONCLUSION

In this paper, the impacts of Connected and Autonomous Vehicles (CAVs) were studied and evaluated using micro-simulation. The driver behavior, car following, and lane changing models were modified to reflect the behavior of CAVs in the widely-used simulation tool, i.e. PTV VISSIM. Three performance measures were collected, namely the average delay, average speed, and total travel time. These measures were used to compare the traffic operation under nine different traffic scenarios. Each of these scenarios was evaluated for eleven market penetration rates, ranging from 0% (no CAVs) to 100% (all CAVs). The results can be summarized as follows:

- The highest benefit of CAVs is reduced average delays reaching up to 86% reduction during off-peak hour conditions.
- Average speed reduction is not affected by traffic volume; as all volume conditions experience somewhat the same change.
- Total travel time reflects the same effect of traffic volume as the average delay (more benefit at lower volumes). However, this effect is lower; reaching up to 23% reduction.
- The highest benefits of CAVs are observed in two stages; first stage at 0% to 20% MPR, and second stage at 70% to 80% MPR.
- The benefits of CAVs are not realized at the same rate as their market share increases. This is probably due to the interactions between regular vehicles and CAVs. These interactions cause driver confusion in regular vehicles as well as sudden and unnecessary breaking by CAVs in some situations, like unexpected lane changes, aggressive driving, or weaving movement.
- Overall, CAV technologies and their utilization show more significant changes at lower traffic volume conditions (off-peak hour). This point matches the findings of similar studies in other regions of the world.

These findings could help decision-makers to understand the expected impacts of CAVs from a traffic operation perspective and could help plan for the adoption of these new vehicles in a way that ensures the highest benefit and lowest risk before they are introduced to the mass market.

The authors recommend further studies to expand on the topic by including more performance measures to evaluate the impacts of CAVs. Another possibility is to investigate the effect of different strategies like dedicated CAV lanes for example.

Change is coming to us whether we like it or not, CAV technologies will affect all levels of society in their daily commutes. Therefore, it is crucial to grasp the limitations and different impacts of the vehicles of the future.

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REFERENCES

Bertini, R. L., Wang, H., Borkowitz, T. M., and Wong, D. H. (2016). 2015 Automated Vehicle Literature Review as Part of Preparing a Possible Oregon Road Map for Connected Vehicle/Cooperative Systems Deployment Scenarios.

Bradburn, J., Williams, D., Piechocki, R., and Hermans, K. (2017). Connected & Autonomous Vehicles: Introducing the Future of Mobility. *Borden Ladner Gervais*, 573–593. https://doi.org/10.1126/science.aal2546

Calvert, S. C., Schakel, W. J., and Lint, J. W. C. Van. (2017). Will Automated Vehicles Negatively Impact Traffic Flow ?, *2017*.

Chen, Y., Gonder, J., Young, S., and Wood, E. (2017). Quantifying autonomous vehicles national fuel consumption impacts: A data-rich approach. *Transportation Research Part A: Policy and Practice*, (xxxx). https://doi.org/10.1016/j.tra.2017.10.012

Chen, Z., He, F., Zhang, L., and Yin, Y. (2016). Optimal deployment of autonomous vehicle lanes with endogenous market penetration. *Transportation Research Part C: Emerging Technologies*, *72*(2016), 143–156. https://doi.org/10.1016/j.trc.2016.09.013

Ilgin Guler, S., Menendez, M., and Meier, L. (2014). Using connected vehicle technology to improve the efficiency of intersections. *Transportation Research Part C: Emerging Technologies*, *46*, 121–131. https://doi.org/10.1016/j.trc.2014.05.008

Shi, L., and Prevedouros, P. (2016). Autonomous and Connected Cars: HCM Estimates for Freeways with Various Market Penetration Rates. *Transportation Research Procedia*, *15*, 389–402. https://doi.org/10.1016/j.trpro.2016.06.033

Talebpour, A., and Mahmassani, H. S. (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transportation Research Part C: Emerging Technologies*, *71*, 143–163. https://doi.org/10.1016/j.trc.2016.07.007

Wadud, Z., MacKenzie, D., and Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice*, *86*, 1–18. https://doi.org/10.1016/j.tra.2015.12.001

Yang, H., Wang, Z., and Xie, K. (2017). Impact of connected vehicles on mitigating secondary crash risk. *International Journal of Transportation Science and Technology*, *6*(3), 196–207. https://doi.org/10.1016/j.ijtst.2017.07.007

Yang, K., Guler, S. I., and Menendez, M. (2016). Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles. *Transportation Research Part C: Emerging Technologies*, *72*, 109–129. https://doi.org/10.1016/j.trc.2016.08.009

Yang, Z., and Pun-Cheng, L. S. C. (2017). Vehicle detection in intelligent transportation systems and its applications under varying environments: A review. *Image and Vision Computing*, *69*, 143–154. https://doi.org/10.1016/j.imavis.2017.09.008

Ye, L., and Yamamoto, T. (2017). Modeling connected and autonomous vehicles in heterogeneous traffic flow. *Physica A: Statistical Mechanics and Its Applications*, *490*, 269–277. https://doi.org/10.1016/j.physa.2017.08.015

Zhang, W., Guhathakurta, S., Fang, J., and Zhang, G. (2015). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society*, *19*, 34–45. https://doi.org/10.1016/j.scs.2015.07.006.