Enhanced short and longer term network performance prediction capabilities through data-driven analytics and simulation:

Simulating the Traffic Impact of AVs and CAVs on Perth's Freeways and Arterial Roads

Submitted to	Main Roads Western Australia & iMOVE CRC
Prepared by	Liam Cummins, Yan Ji, Chao Sun, Thomas Stemler, Doina Olaru, Sharon Biermann
Submitted by	Chao Sun (chao.sun@uwa.edu.au), Planning and Transport Research Centre (PATREC)
Steering Committee	Kamal Weeratunga, Steve Atkinson, Graham Jacoby and Chao Sun
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EXECUTIVE SUMMARY

As Australia's transport ministers 'have agreed on the strategic priority of preparing for the deployment of automated vehicles and other innovative transport technologies' (Australian Government, 2019), it becomes more important than ever to understand the implications of these technologies and what they mean to our planning practices. Although praised for their foreseen ability to 'solve' our traffic woes, disruptive technologies such as Automated Vehicles (AVs) and Connected and Automated Vehicles (CAVs) also bring many uncertainties. Governments often plan decades ahead and the uptake of AVs/CAVs is likely to happen within our planning horizon. Hence, any long term investments without adequate consideration of their potential impact are inherently risky. It is reasonable to question whether planned major transport infrastructure will be appropriate in accommodating and facilitating a fully automated future.

Understanding the potential impact of AVs and CAVs will help us future-proof infrastructure investments and mitigate policy risks. Transport agencies do not have direct control over the development of technologies per se, but by providing the necessary infrastructure and enabling environment through appropriate policy settings, they can choose the desirable future from many forecast scenarios and work backwards to design policies and programs to achieve it. This is a concept known as backcasting.

While car technology developers focus more on the engineering of individual AVs and CAVs, it is up to governments to assess and respond to their systematic impacts. This project marks the first step towards modelling the potential traffic impacts of AVs and CAVs on Perth's freeways and arterial roads. Main Roads Western Australia supplied three traffic models for testing – Mitchell Freeway, Stirling Highway and Canning Highway. The models were calibrated to reflect the current situation with 100% human-driven vehicles (HDVs) which served as the base case. They are representative of typical freeways and arterial roads, so the results are assumed to be generalizable across the Perth road network. Two AV (AV1 and AV2) and one CAV driving models derived from the literature were programmed into the modelling package Aimsun by the research team for scenario testing. The aim was not to predict the precise future but to estimate the range of possibilities by establishing the upper and the lower bounds that form the best- and worst-case scenarios. The results would also help determine the scale of potential improvement that AVs and CAVs could bring.

The significant findings of this research are:

- Both AVs and CAVs could improve the operations of both freeways and arterials but more so, freeways. This is despite the fact that they were tested using a wider range of performance parameters than human-driven vehicles (e.g. lower acceleration and deceleration rates to improve comfort, see Appendix Table 2). The results imply increased road capacity when AVs and CAVs are prevalent but the disproportionate increase between freeways and arterials could cause a mismatch between their performance which may lead to bottlenecks at places where they connect (i.e. ramps).

- The best case scenarios were produced by CAVs at 100% market penetration with significant improvement. The average delay (the difference between actual travel time and free-flow travel time) on the Mitchell Freeway was reduced from the current value of about 28 sec/km to just 1 sec/km, about 96% reduction from the base case of 100% HDVs. For Canning Highway, it was the difference between 89 sec/km and 41 sec/km, less dramatic but still a 54% reduction over the base case. Stirling Highway results are similar to Canning Highway's.
- 100% CAVs not only significantly improved the traffic operations but also travel time reliability, leading to more predictable journey times.

Canning Highway results show that increasing AV1 and CAV market shares, both reduce the average delay time compared to the base case of 100% HDVs, with CAV outperforming AV1 at every level. CAVs at 60% market penetration can delivery almost the same performance to AV1s at 100% market penetration (Table 3 and Figure 11). For freeways, it would take even lower percentage of CAVs to match the performance of 100% AVs, since CAVs benefit freeways more than arterials. Although the 80% CAV scenario has a reasonably close average performance to the 100% CAV scenario, only the latter avoided any significant spike altogether and produced much more constant traffic condition throughout the whole simulation period (6:45 – 9:45) for the Canning Highway model. This suggests that the last 20% connectivity is important in realising its full potential.

- Reaction time appears to be the most significant factor affecting performance among all simulated variables. CAVs benefited largely from having zero reaction time in the simulations. Although our literature search suggests that CAVs and AVs can achieve shorter reaction times than human drivers, if reaction time is set by the user to be slower for purposes of comfort etc., it is possible that they (especially AVs) could perform worse than HDVs.
- There might be unintended consequences. For example, the high density flow achieved by a platoon of CAVs could create difficulties in merging and lane changing because gaps between CAVs are too small for vehicles in adjacent lanes to get into, as illustrated in Figure 12.

The best-case scenario is likely to be an overestimate but the potential performance improvement of AVs and CAVs does mean certain road capacity expansion might be avoided or delayed. It is advised that the technology-readiness for uptake of AVs/CAVs is regularly assessed and that business cases should account for their impact when mass deployment is within reach. We have chosen three AV/CAV driving models from the current literature. However, they might not remain the best choices as technology advances and our understanding improves. Therefore, this research should also be updated when new information about AV and CAV driving behaviour is available.

This project mostly focuses on the supply side changes, i.e. how much would AVs and CAVs change the road capacity. However, changes to the demand side including human factors are arguably more important because they are less predictable and the consequences are far reaching. For example, some people might choose to extend their CAV's car-following distance and consequently lower network performance because they do not feel comfortable travelling too closely behind another vehicle. Fully automated vehicles are also expected to induce demand since they lower people's perceived value of travel time by enabling them to make better use of their in-vehicle time. The currently mobility restricted population could also have the new-found freedom to travel independently. Although these could have positive social and economic benefits, the induced demand will at least partially offset the potential capacity increase. Wider implications such as the potential of worsening urban sprawl also need to be carefully assessed.

Demand modelling with so many uncertainties will require another full-scale study, which is beyond the limited scope of this project. Instead of estimating what is likely to happen, we conducted a sensitivity analysis to test how much extra demand that 100% AVs and CAVs could cope with, while maintaining similar average delay times to the current 100% HDV scenario. The results show that 100% CAVs could accommodate an increase of about 80% and 50% in traffic volume on Mitchell Freeway and Canning High respectively. By comparison, 100% AV1s could only accommodate 5% and 15% additional demand respectively. This again highlights CAVs' advantage over AVs. It also shows that it does not take 1% increase in demand to cancel the 1% reduction in delay time.

Compared to V2I (vehicle-to-infrastructure), V2V (vehicle-to-vehicle) as a consumer technology has the advantage of not requiring expensive public infrastructure and its maintenance costs. Since our CAV model results show V2V plus some simple V2I technologies alone could make significant improvement to the network, further research needs to examine whether this diminishes the necessity for more sophisticated and expensive V2I technologies. Another suggested extension of the research is simulating the operations of dedicated AV lanes on Perth's freeways. Demand changes including land use implications should also be modelled more thoroughly when a fully calibrated LUTI (Land Use and Transport Interaction) model for Perth is available.

The research presented in this report delivers on Subproject 2 of a larger research project comprising two sub-projects:

- Subproject 1: Data-driven empirical models for short-term traffic prediction (Part 1) and non-route-based area optimisation of network productivity (Part 2)
- **Subproject 2: Simulating the traffic impact of AVs and CAVs to Perth's freeways and arterial roads**

This research was funded by PATREC and the iMOVE CRC and supported by the Cooperative Research Centres program, an Australian Government initiative. Supplementary funding was provided by Main Roads Western Australia to extend the simulation to include impacts of CAV (in addition to AVs alone) and impacts on arterials (as well as freeways). The contribution of the steering committee throughout the project, in guiding, monitoring and review, is gratefully acknowledged.

1 INTRODUCTION

1.1 BACKGROUND

The iMOVE project 1-003, *Enhanced short and longer term network performance prediction capabilities through data-driven analytics and simulation,* was co-funded by the following organisations:

- Planning and Transport Research Centre (PATREC)
- Main Roads Western Australia (Main Roads)
- iMOVE CRC
- The University of Western Australia (UWA)

The project comprised two subprojects:

- Subproject 1: Data-driven empirical models for short-term traffic prediction (Part 1) and non-route-based area optimisation of network productivity (Part 2)
- **Subproject 2: Simulating the traffic impact of AVs and CAVs to Perth's freeways and arterial roads**

This report summarises the findings of Subproject 2.

The kick-off meeting was held on 12 February 2018 during which the project steering committee was formed comprising:

- Kamal Weeratunga (Committee Chair) / Manager Network Performance (Acting), Main Roads
- Graham Jacoby / Network Operations Analysis Manager, Main Roads
- Steve Atkinson / Principal Analyst Strategic Planning, Main Roads
- Chao Sun / Research Follow (Project Leader), UWA

The committee met monthly with other invitees to discuss the progress and make decisions. The project started officially in March 2018.

1.2 PROJECT BRIEF

AVs (Automated Vehicles) and CAVs (Connected and Automated Vehicles) are increasingly closer to impacting our road networks. Modelling commissioned by the Queensland Department of Transport and Main Roads predicted that Australia's fleet of vehicles will be 50% autonomous approximately between 2040 – 2050 extending to 100% by 2050-2060 (TransPosition 2016). As Australia's transport ministers 'have agreed on the strategic priority of preparing for the deployment of automated vehicles and other innovative transport technologies' (Australian

Government 2019), it becomes more important than ever to understand the implications of these technologies and what they mean to our planning practices.

Traditional vehicle and parts manufacturers, start-ups, ride hailing and technology companies are developing AV and CAV technologies, with levels of investment of at least tens of billions of dollars over the past decade (McKinsey & Company 2019). Whilst most technology developers focus on making AVs/CAVs safe, operational and comfortable to consumers, it is important for governments to understand their system effect on the wider network, especially once they become a more prevalent transport choice.

There are a range of perspectives about how CAVs will impact on existing road networks. At either end of the spectrum these include:

- Utopian style 'shared robo taxi' services where car ownership is non-existent, rides (not just vehicles) are shared more readily, hence vehicle occupancy increases to the point that congestion is eliminated.
- Dystopian futures where urban sprawl worsens due to consumers owning and operating CAVs where they are prepared to spend longer in a vehicle each day as they are freed from the driving task and can be more productive during their commute. This scenario could worsen congestion.

There are a number of unknowns around the commercial deployment of AVs and CAVs. These include:

- **Business model** – Those commercialising the technology might chose to sell vehicles to the public, or operate their own 'robo taxi' fleet providing transport as a service in a similar manner to existing taxis and ride hailing companies, but at a substantially cheaper rate.
- **Pricing** – One of the promises of the technology is to provide transport services at a lower cost, potentially shifting demand from owning vehicles to transport services. However, without understanding underlying costs it is difficult to predict mixes of vehicle fleets and thus impacts on the network.
- **Technology** – Different manufacturers have different technologies that acquire and process surrounding information differently with various levels of precision and delay before actuating it into vehicle movements. Much of the technical information is proprietary and AV/CAV behaviour is not directly observable due to their very limited presence on the current road network.
- **User preferences** – Some manufacturers offering semi-autonomous features already offer customisable settings (for example following distance). While a technology may be safely able to reduce headway, if customers are allowed to select their own settings and prefer a larger distance, the expected benefits may not occur.

Governments often plan decades ahead for major infrastructure investments. Although predictions vary widely, experts seem to agree that the uptake of fully automated vehicles will happen within our planning horizon (Transport for NSW n.d.). It is therefore reasonable to question whether planned major transport infrastructure will be appropriate in a fully automated future. Understanding the potential impact of AVs and CAVs will help us future-proof infrastructure investments and mitigate policy risks. Any long-term investments without adequate consideration of their potential impacts are inherently risky. Transport agencies do not have direct control over the development of technologies per se, but they can choose the desirable future from many forecast scenarios and work backwards to design policies and programs to achieve it, a concept known as backcasting.

Detailed microsimulation experiments are the most cost-effective method to test future traffic scenarios whilst still producing realistic results. Unlike some other more abstract models, each vehicle's movement is explicitly simulated at every time step. Utilising real demand data, road infrastructure and driving models derived from the literature, the predicted effects on traffic performance can be analysed. The broader demand side uncertainties such as consumer adoption rates, vehicle ownership, demand changes were outside of the scope of this project.

This project marks the first step towards modelling the potential traffic impact of AVs and CAVs on Perth's freeways and arterial roads. The aim was not to predict the precise future but to estimate the range of possibilities by establishing the upper and the lower bounds that form the best- and worst-case scenarios. The purpose of the project was to quantify the impact on Perth's road network if CAVs and AVs were mixed in with human-driven vehicles (HDVs) considering current levels of demand and infrastructure. Main Roads Western Australia supplied three Aimsun (the traffic modelling package) models for testing – Mitchell Freeway, Stirling Highway and Canning Highway. They are representative of typical freeways and arterial roads, so the results are assumed to be generalizable across the Perth road network. By analysing changes in traffic performance, we can understand their impacts and better plan for when these technologies are actually employed.

1.3 TERMINOLOGIES

AVs and CAVs

There has been much confusion regarding to the terms automated, autonomous, self-driving and driverless, even among experts in the field. This report adopts the view (e.g. Levinson 2017) that 'autonomous' and 'driverless' vehicles are those which achieve full driving automation under specified conditions or all conditions, Level 4 and 5 respectively according to the SAE International (2018) taxonomy, so they do not require human intervention when operating in those conditions; while 'automated' and 'self-driving' vehicles range from Level 1 to Level 5 automation. We used the term 'automated' in this report to reflect the fact that the impact of AVs/CAVs on the road network do not necessarily require full autonomy. In fact, traffic impacts reported in this report could be realised as long as the vehicle's longitudinal movement is automated (generally in the form of Adaptive Cruise Control for Level 1 and above).

Connected Vehicles (CVs) and Automated Vehicles (AVs) are two distinct technologies. Although most AVs will probably have some internet connectivity for tasks such as software updates, they do not necessarily rely on it for its operation. In this report, AVs refer to those automated vehicles that solely rely on its local sensors to respond to stimuli. CAVs on the other hand combine CV and AV technologies. They have the capability of communicating with nearby vehicles and/or infrastructure, and automatically use it to make decisions. The advantage is reduced vehicle reaction time (to near zero) as the required information is directly transmitted rather than sensed.

Driving behaviour by CAVs, AVs and humans are distinct from each other. Variations also exist within each group. Each vehicle within these separate classes will also be expected to behave differently according to various vehicle-intrinsic capacities and user settings. Due to these reasons, previously used driving models and parameters that only represented human driving cannot sufficiently capture the effects AVs and CAVs will cause. Hence, more appropriate driving models designed for AV and CAV were adopted. We modelled two types of AVs and one type of CAV, referred to as **AV1**, **AV2** and **CAV** in the report. Although **AV1** and **AV2** both operate using their own, unconnected sensors, **AV2** was specifically designed to dissipate stop-and-start shock waves in traffic (more details in the Appendix). All AV and CAV models only simulate behaviour on the longitudinal direction so other aspects of driving such as lane changing are not considered due to limited information available in the literature. Human-driven Vehicles (HDVs) were simulated by Aimsun's default model that was formulated to mimic human driver behaviour. The original Main Roads models all run 100% HDVs and they serve as the base cases that reflect the current situation. AV1, AV2 and CAV models were programmed by the project team using Aimsun's microSDK extension package and C++ programming. More detail on the driver behaviour models is provided in the appendix.

V2V and V2I

The two main forms of vehicle connectivity are vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. This research only considers the simplest V2I communication by which traffic signals broadcast their status to queueing CAVs so that they can react immediately when lights turn green. Other more advanced applications such as using V2I for optimising network operations is beyond the current scope.

In terms of V2V, vehicles in the model can only communicate with their immediate neighbours in the same lane. It requires both the leading and following vehicles to be CAVs. The following CAV acquires the velocity and acceleration of the CAV in front of it with no communication delay. However, when a CAV follows a non-CAV, the follower will instead have to fall back to its local sensors (with their associated delays) and switch its driving behaviour to the AV1 model. The CAV mode will be turned back on when it gets a new CAV as its leader.

Microsimulation

All models involved in this project are so-called microsimulations. Unlike some other more abstract models, microsimulation involves explicitly simulating each vehicle's movement and decisions at every time step (every 0.1 second in our case) so that its interaction with other vehicles and the infrastructure can be modelled in detail. In the meanwhile, system performance can be analysed at different levels so it is the most appropriate tool for this research. Microsimulation models are stochastic in nature, meaning the model outputs can vary even if model parameters are held constant. This feature is designed to capture the natural variability caused by random events. It explains why bands were used in some figures in Section 3 to show the range of performance related to the best and worst case scenarios.

Delay time

Delay time was chosen as the metric to measure the traffic performance between scenarios, although other metrics such as average speed are also reported in Section 3. It is commonly used in traffic engineering and is calculated as the time difference between actual travel time and free-flow travel time. Less delay means less wasted time in traffic so the best case would have the lowest delay and the worst case would have the highest. For freeways, delay is the result purely of interaction between vehicles. Delays on arterials are caused by traffic control devices such as intersections as well as vehicle interactions. The average delayed is calculated as per vehicle and across distance (sec per km).

Reaction times

Reaction time is the time it takes a vehicle to react to speed changes of its lead vehicle. For a given speed, shorter reaction time leads to shorter physical gaps between succeeding vehicles, which produce higher vehicle density (measured by veh/km) and higher traffic flow (measured by veh/hr), as illustrated in Figure 2. Reaction time at stop is the time it takes a stopped vehicle to react to the acceleration of the lead vehicle. Reaction time at traffic signal is the time it takes the first stopped vehicle at a traffic signal to react when turning green. Vehicle reaction times have significant impact to the system performance (see Section 2.2 and the Appendix).

SCATS

Sydney Coordinated Adaptive Traffic System (SCATS) is the current traffic control system used in Western Australia and most other Australian jurisdictions. It is an adaptive system that can change traffic signal settings according to different traffic conditions. It is worth noting that traffic signals in our arterial experiments are assumed to operate under fixed timing as opposed to the real SCATS adaptive control regime. This is because the times considered in the experiment are during the morning rush hour, during which the traffic is saturated so SCATS tends to behave much like a fixed-timing system.

2 EXPERIMENT METHODOLOGY

By means of microsimulation experiments within the Aimsun models, analysis of traffic performance on some of the main roads of the Perth network caused by changes to the future vehicle mix can be conducted. Results can then be used as an indicator of how the wider network could be affected and implications for forthcoming years.

Traffic microsimulation is computationally intensive so it was not practical to cover all possible scenarios. To find the upper and lower bound of possibilities, an optimisation algorithm invented by Google was adopted to guide the search for those extreme cases quickly (Baltz et al. 2017). Through varying the percentages of different types of modelled vehicles and the parameters that govern them, the algorithm was able to find the combinations that produced the best and worst cases. As mentioned in Section 1.3, delay time is used as the metric to measure traffic performance.

2.1 PERTH AIMSUN ROAD NETWORK

Freeways and arterials are significantly different in the way they operate so it is important to include both categories. The three Aimsun models (Mitchell Freeway, Canning Highway, Stirling Highway, see Figure 1 for their locations) had been previously developed and calibrated by third-party consultants for Main Roads. Each road has been modelled in detail in terms of geometric shape, form and size. The models also include all the roads that directly branch off/onto the road section of interest, although truncated. This is so that results obtained correspond directly to the section of interest as well as ridding the simulation of unnecessary complexity and related computational expense. Included in the models are the associated bus service lines that operate in them with correct schedules. The modelled traffic control devices include traffic signals, stop signs, give ways, speed limits, yellow box junctions, bus lanes and bus stops.

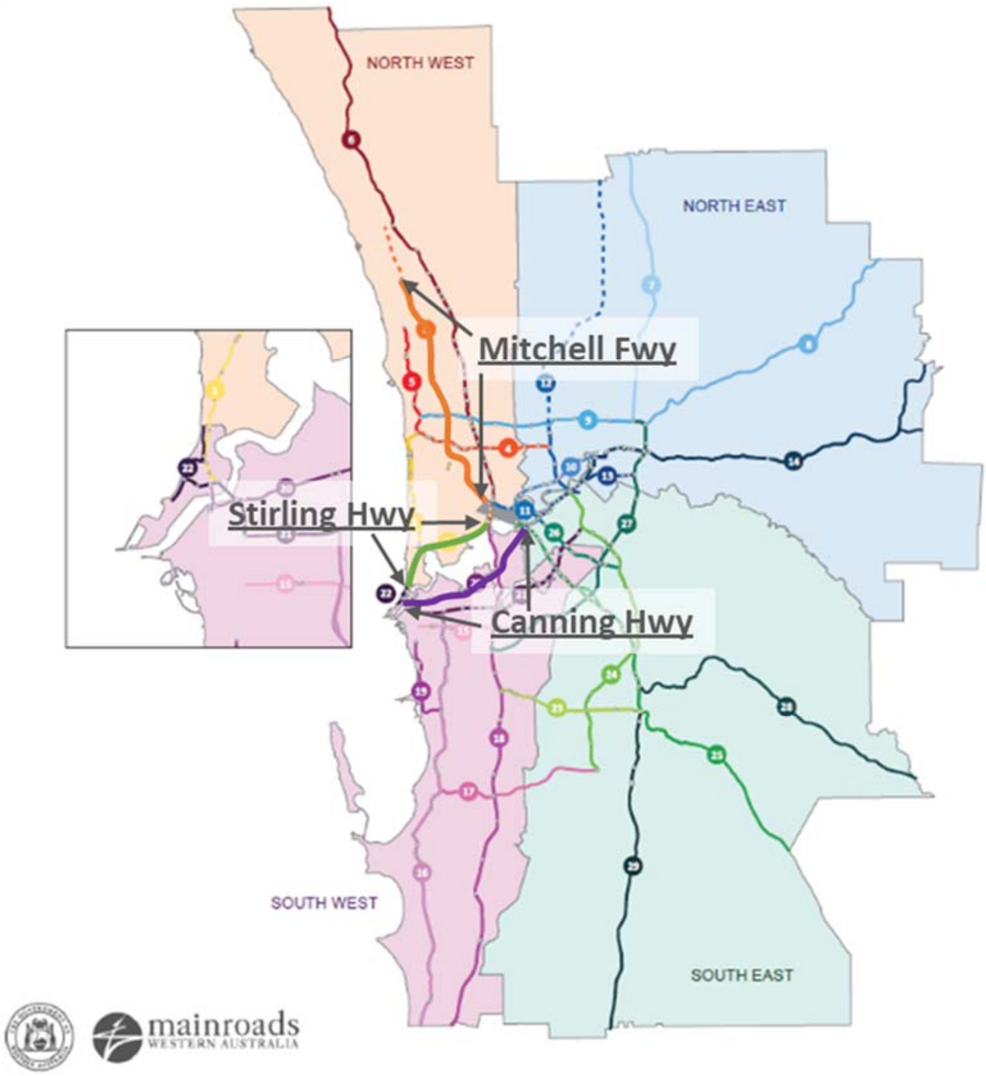

Figure 1 The indicative location of Mitchell Freeway, Canning Highway and Stirling Highway (Main Roads Western Australia 2018)

The Mitchell Freeway results presented in the report only include southbound traffic during the AM simulation period (5:00 – 9:30am). The southbound and northbound traffic peak at different times so it was decided to focus on one direction only. It also significantly shortened the computing time. The arterial road experiments were conducted for both directions in the AM period (6:45 – 9:45am). In both cases, the simulation period was adopted from Main Roads' original models.

2.2 MODEL PARAMETERS

Microscopic modelling involves the updating of vehicles' speed and position within the model environment which entails many parameters and often complicated mathematical formulas. The Appendix contains more detailed discussion of different models used in this research and the range of values used for the most important parameters. It is important to note that due to larger uncertainties surrounding the performance of AVs and CAVs, we have assigned a wider range of variation to some of the parameters, especially those related to reaction time, acceleration and deceleration. This is partially because these fast evolving technologies have not been rolled out to the mass market so there is not enough observation of their performance. The uncertainties are also caused by how people might use them. For example, some authors (Le Vine et al. 2015) are concerned about the possibility that humans might want to slow down their AVs/CAVs for better comfort and reduced chance of motion sickness so that they can work when their vehicle drives itself. This is exemplified in Hyundai's latest technology development in adaptive cruise control, which first monitors and then aims to mimic the user's unique driving style (Lavars 2019).

Consequently, a rather large range of variations was set for AV/CAV acceleration and deceleration rates. For example, the mean (average) max acceleration (see the Appendix for more details) for AVs and CAVs on the arterials are set to between 1.2 and 3.8 m/s^2, as opposed to a fixed mean value of 3.8 m/s^2 for HDVs. The latter is fixed because it is directly observable from existing vehicle behaviour. It is important to understand that individual vehicles will still draw their actual acceleration values from the corresponding normal distributions so not all HDVs use the same number, i.e. there are individual differences but their average max acceleration is 3.8 m/s^2. By contrast, the AV/CAVs have variable means, which lead to a wider range of possible values. The same applies to other AV/CAV parameters with variable means in the Appendix.

The minimum AV/CAVs longitudinal acceleration and deceleration values of 1.2 m/s^2 and –1.2 m/s^2 coincides closer to the recommended values light-rail uses to ensure passenger comfort levels (Transit Cooperative Research Program 2012; Xiao et al. 2017). Le Vine et al. (2015) used values similar to high-speed rail, approximately ± 0.5 m/s^2, though this is not considered as it is presumed by the project team to be too extreme since it is deemed unlikely that an average AV user will slow it down by that much. Furthermore, this experiment only models for longitudinal acceleration and deceleration though CAVs could potentially be limited further when considering lateral accelerations.

In Figure 2, an example of the effects that a one second reaction time has on vehicles, is compared to having no reaction time at a traffic signal turning green. It is observed that with a one second reaction time, once the light changes green, a wave of vehicles beginning to accelerate, travels downstream of the intersection – initially two vehicles cross the stop line, followed by another two at t2. In contrast, with no reaction time, all vehicles are able to coordinate their movement simultaneously (this is what CAVs can achieve), resulting in double the number of vehicles crossing the stop line (four vehicles at t1 and almost eight at t2). The lower the reaction time is, the higher the saturation flow (maximum possible throughput), meaning that more vehicles can pass through each green signal phase so the capacity will be higher for the same intersection.

Figure 2 An illustration that shorter reaction time can increase the throughput at a traffic light

Human drivers' reaction times at stop signs and at traffic signals are longer than during normal driving because they switch off and react slower. AVs and CAVs are presumed not to have this problem, as reflected in Table 5 (Appendix).

Literature suggests AVs' sensors and mechanical controllers are faster-acting than humans, though the actual values reported are not strongly consistent. Some research has attributed a delay of 0.1 – 0.2 seconds to sensors and 0.1 – 0.3 seconds to mechanical actuators resulting in a total reaction time (sensor plus actuator) range of between 0.2 and 0.5 seconds (Ploeg, Van De Wouw & Nijmeijer 2013; Rajamani 2011; Wang et al. 2018; Xiao & Gao 2011). 0.5 seconds is accordingly used as the upper limit for AV reaction times. However, based on possible technological advancements to improve reaction time of sensors and controllers in future, a lower limit of 0.1 seconds is used (Table 5, Appendix). It is also the lowest value allowable in Aimsun.

As AVs/CAVs have predetermined behaviour, they are expected to follow the rules of the road. Hence the speed acceptance (i.e. compliance to speed limit) value is set to a value of 1 so that speed limits are the actual limits of the vehicles speed.

3 RESULTS AND DISCUSSION

As discussed in Section 2, an optimisation algorithm was used to find the upper and lower bounds quickly, using vehicle delay time as the metric. It confirmed that in all cases having nearly 100% HDVs will produce the worst-case scenario with the highest delays and having nearly 100% CAVs will produce the best-case scenario with the lowest delays, with 100% AVs falling in between[1]. Manual simulation of 100% HDV and 100% CAV scenarios showed very similar results. Since the base case with all HDVs remains the worst case, any substantial addition of AVs and CAVs is likely to improve traffic, as long as the assumptions made in Section 2.2 and the Appendix are valid.

Far more significant, however, are the results relating to what happens between the best and worst cases and the absolute differences in performance. The simulation experiments enabled testing of impacts relating to the application of a variety of performance parameters; the relative performance of AVs; variable impacts on particular performance measures; the scale of performance impact measured in absolute terms and the impacts of different driver behaviour model mixes.

The experiments allowed AVs and CAVs to be 'disadvantaged' by being given a wider range of performance parameters than HDVs (e.g. lower acceleration and deceleration rates for improved comfort, see Appendix Table 2), which according to some authors (e.g. Le Vine et al. 2015) might produce performance lower than that of HDVs. The reason that we did not reach the same conclusion as in Le Vine et al. (2015) that 'slower AVs' might compromise intersection performance is probably because the range of acceleration and deceleration rates we used is not as extreme as theirs (Section 2.2). Our experiments instead suggest that reaction times have larger impact than other vehicle performance parameters (Section 3.3.1). Based on our previous research (Cummins 2018), the project team was also concerned that some AV and CAV driving models might become counterproductive under certain congested traffic conditions because they cannot handle aggressive human driving behaviour, especially lane changing. This has been shown in Cummins (2018) mixing AV2s with HDVs on an idealised ring road model. The addition of AV2s worsened traffic operation in most scenarios. Nevertheless, it did not eventuate in our experiments using Main Roads models, which should be further investigated in future research.

More important than ranking the performance of AVs, CAVs and HDVs, the research quantified the scale of possible improvements that AVs and CAVs could bring to freeways and arterials respectively. For example, 100% CAVs could reduce the average delay time on Mitchell Freeway by about 96% compared to HDVs, while it would have a less dramatic but still significant reduction of 54% on Canning Highway. Section 3.1 and 3.2 contain more detailed results, with Section 3.3 highlighting a few important observations.

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[1] The reason that these totals are not exact 100% is due to the limitations of the optimisation algorithm – it can find 'good enough' but not 'absolute' answers.

3.1 FREEWAY RESULTS

Table 1 shows that the best-case scenario (near 100% CAVs) for Mitchell Freeway not only achieved a dramatic decrease in delay time (1sec/km versus 28 sec/km in the case of worst case) but also excelled in all other measures (Figure 2). Its average speed is only 6 km/hr lower than the speed limit, compared to 54 km/hr below the speed limit in the worst case of near 100% HDVs. The stop time is 0 second/km (or close to 0), indicating the total absence of stop-and-start congestion on the freeway. It also has the lowest vehicle density of 14 veh/km compared to 23 veh/km in the case of near 100% HDVs.

Table 1 Vehicle composition and average delays for the best- and worst-case scenario (Mitchell Freeway southbound, 5:00 – 9:30AM)

	Vehicle Composition	Average Delay (sec/km)
Best Case Scenario	Near 100% CAVs	1
Worst Case Scenario	Near 100% HDVs	28

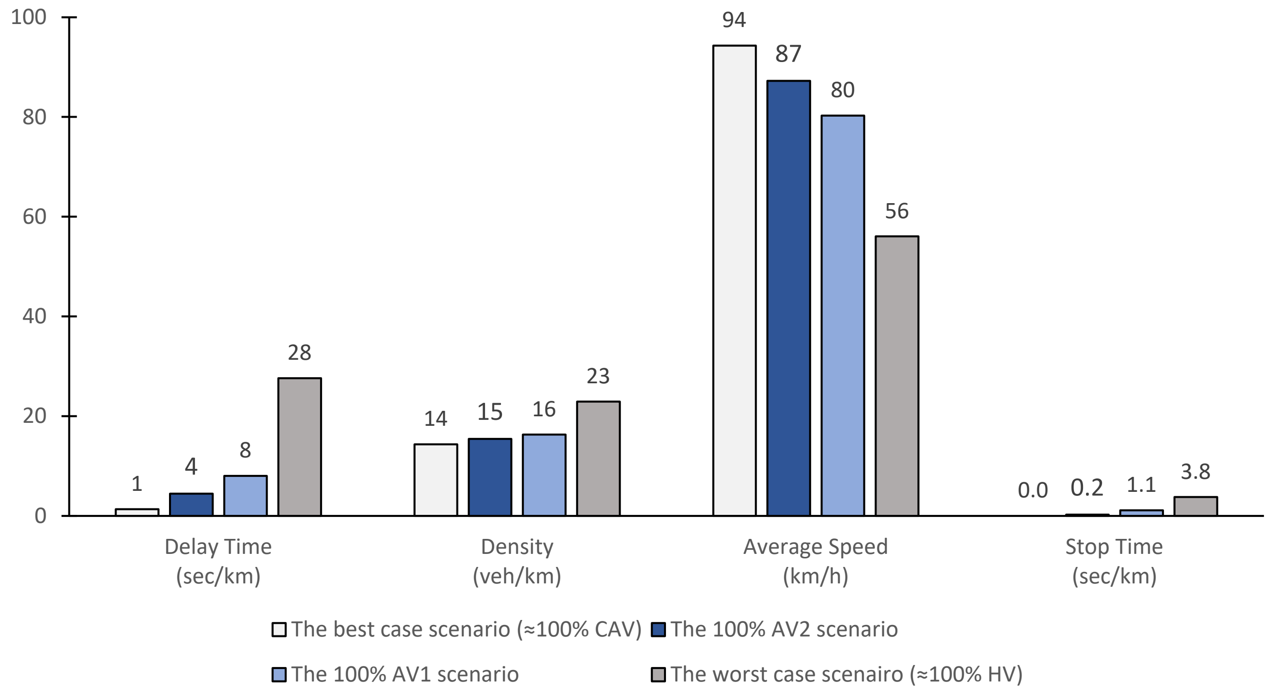

Figure 3: Performance comparison of different scenarios (Mitchell Freeway southbound, 5:00 – 9:30AM)

Figures 4 to 6 show the evolution of traffic condition during the AM simulation period. The highest (100% HDV) and lowest delay (100% CAV) ‘extreme’ cases are each represented by two lines that define a band of performance showing how much conditions could vary over time. Bumpy lines indicate higher intra-day variations, meaning cars travelling during the same AM period will experience large differences in delay time. Meanwhile, wider bands signify higher inter-day variability, meaning delay between the same period of different days could be considerably different even if traffic demand stays the same (this is a reflection of the random nature of traffic, as discussed in Section 1.3). The much smoother lines and narrower band of the 100% CAV scenario imply more stable traffic conditions that lead to more reliable journey times for road users.

AV1 and AV2 at 100% market penetration did not produce the extreme cases so the figures include results of additional simulations which were manually conducted to show their relative performance. 100% AV2s outperformed 100% AV1s by all measures (Figure 3; Figure 4). To avoid cluttering, their results in Figures 4, 5 & 6 are only represented by single lines that show the average performance in between the two extremes.

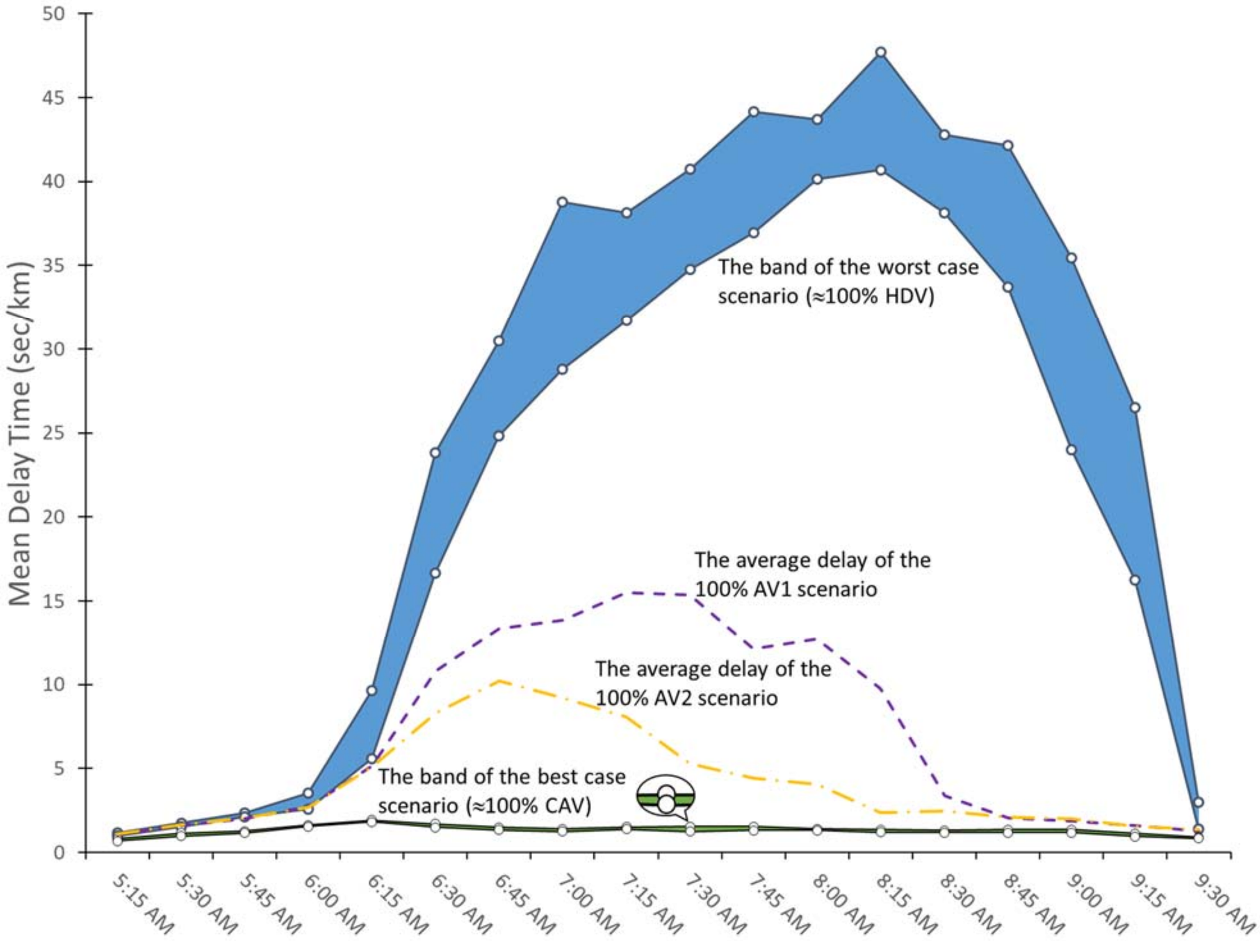

Figure 4: Time series of mean delay times for different scenarios (Mitchell Freeway, southbound, AM)

Note:
Results of the highest delay (worst case, 100% HDV) and the lowest delay (best case, 100% CAV) scenarios were derived from five simulations each. Their associated bands show the range of variability between simulations, which represents inter-day variability (how much delay time varies within the AM period). *The band of the 100% CAV scenario is too narrow to be seen clearly because the results do not vary greatly.* The 100% AV1 and AV2 results are represented by lines showing their average performance.

The average speed has an inverse relationship with delay. 100% CAVs can achieve the highest average operating speed, followed by 100% AV2, 100% AV1 and lastly 100% HDV (Figure 5).

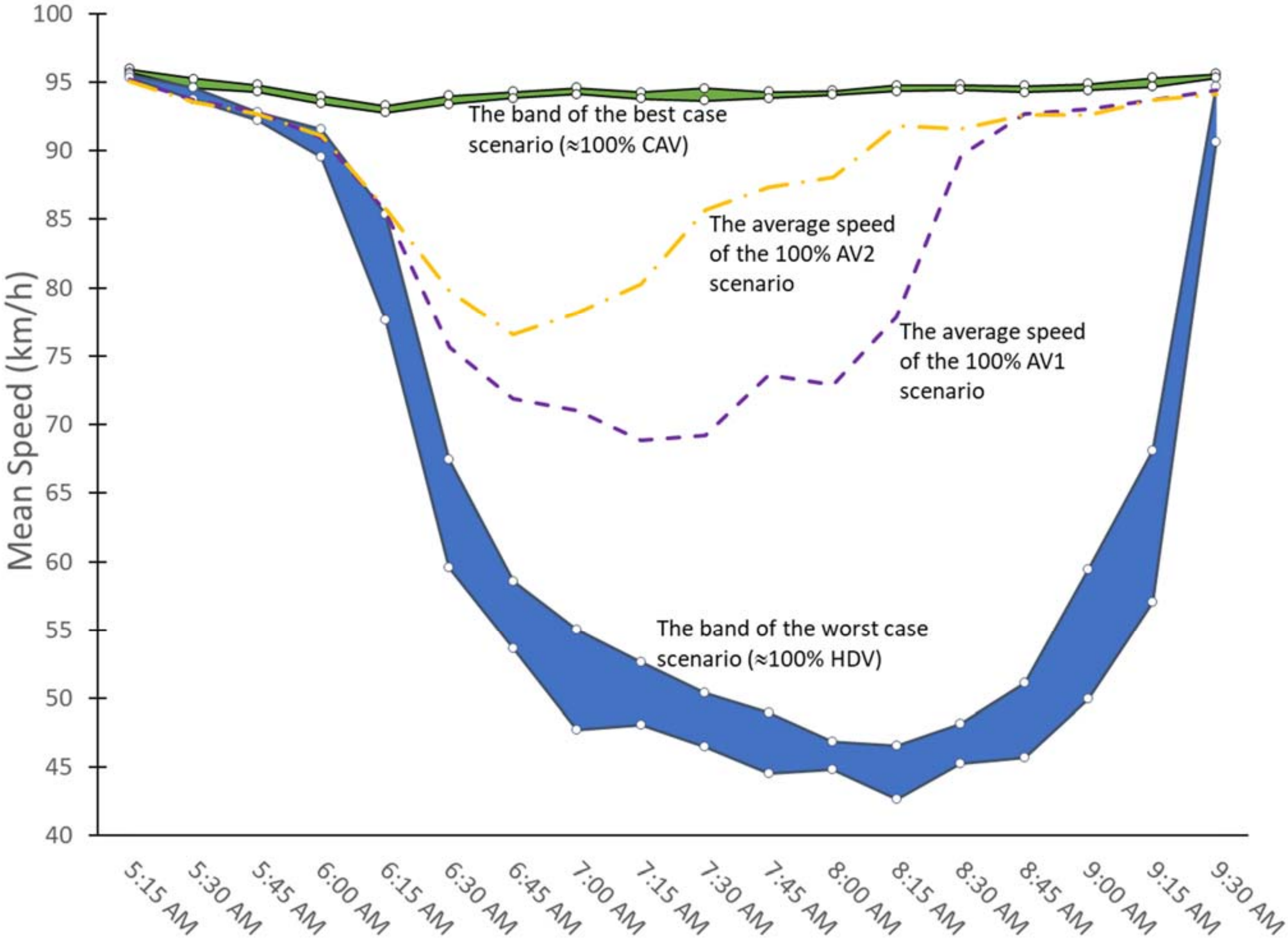

Figure 5: Time series of average speed for different scenarios (Mitchell Freeway, southbound, AM)

Note: as in Figure 4.

Figure 6 shows the average vehicle density of the 100% CAV and 100% AV scenarios stayed relatively flat throughout the entire simulation period and was considerably lower than the 100% HDV most of the time. Lower density indicates that CAVs and AVs can provide a substantial amount of spare capacity above the current demand.

In Figures 3 to 5, the biggest differences are at the height of the peak with smaller differences at the start and end because of the associated lower demands. The 100% CAVs case peaked the earliest (although almost not visible), followed by 100% AV2s, 100% AV1s and lastly 100% HDVs. In comparison to HDVs, CAVs and AVs demonstrate lower levels of congestion build-up, avoiding the need for excessive recovery.

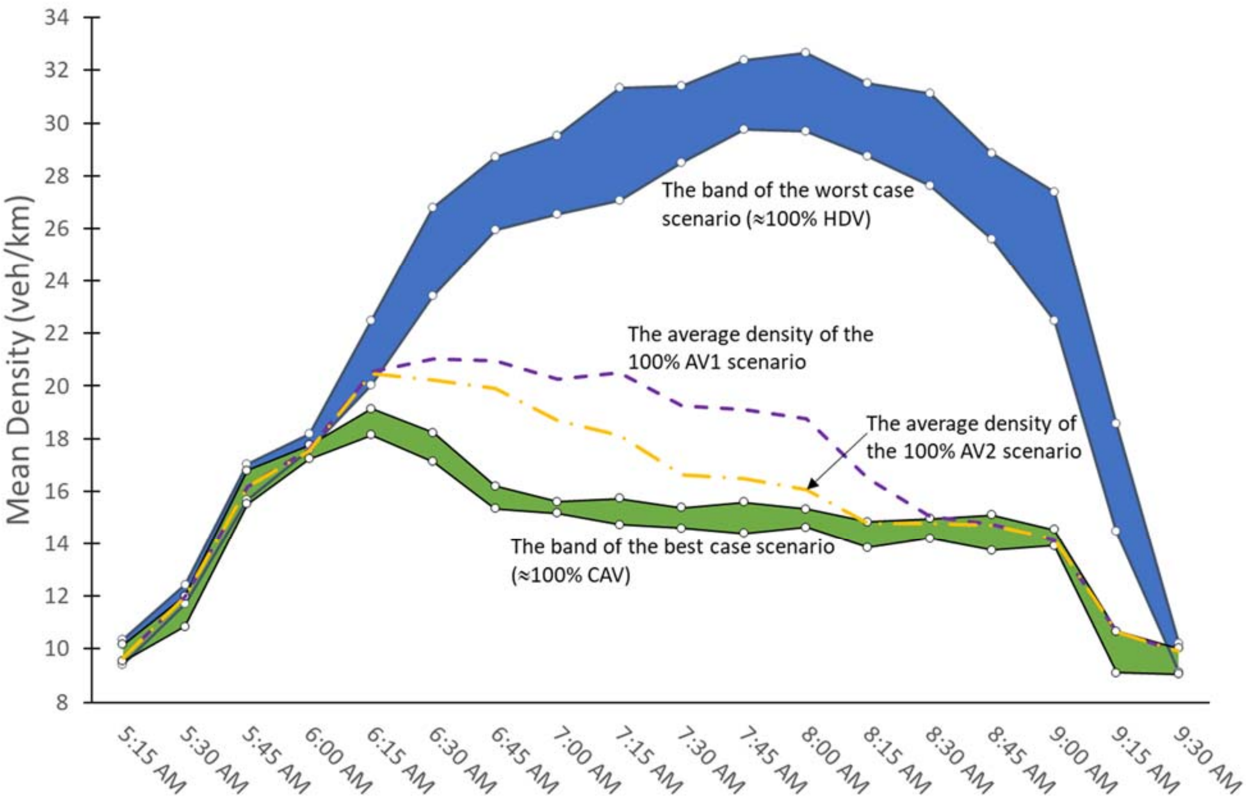

Figure 6: Time series of mean density for different scenarios (Mitchell Freeway, southbound, AM)

Note: as in Figure 4.

3.2 ARTERIAL RESULTS

Canning Highway and Stirling Highway showed similar relative results so only the former is reported here to be concise.

Similar to the freeway results, the near 100% CAV scenario produced the best results for arterials, although the relative improvement is less dramatic than for the freeways. The near 100% HDV scenario still has the worst-case traffic performance in terms of delay time. Similar to the freeway results, the 100% AV1 scenario sits in between them. AV2 was not simulated since it is not designed for arterial traffic.

Table 2 Vehicle composition and average delays for the best- and worst-case scenario (Canning Highway, 6:45 – 9:45am)

	Vehicle Composition	**Average Delay (sec/km)**
Best Case Scenario	Near 100% CAVs	41
Worst Case Scenario	Near 100% HDVs	89

Figure 7 shows that the mean delay time and stop time of vehicles of the best-case scenario is less than half of the worst case. Vehicle density was reduced to about two thirds and average speed was increased by the same factor.

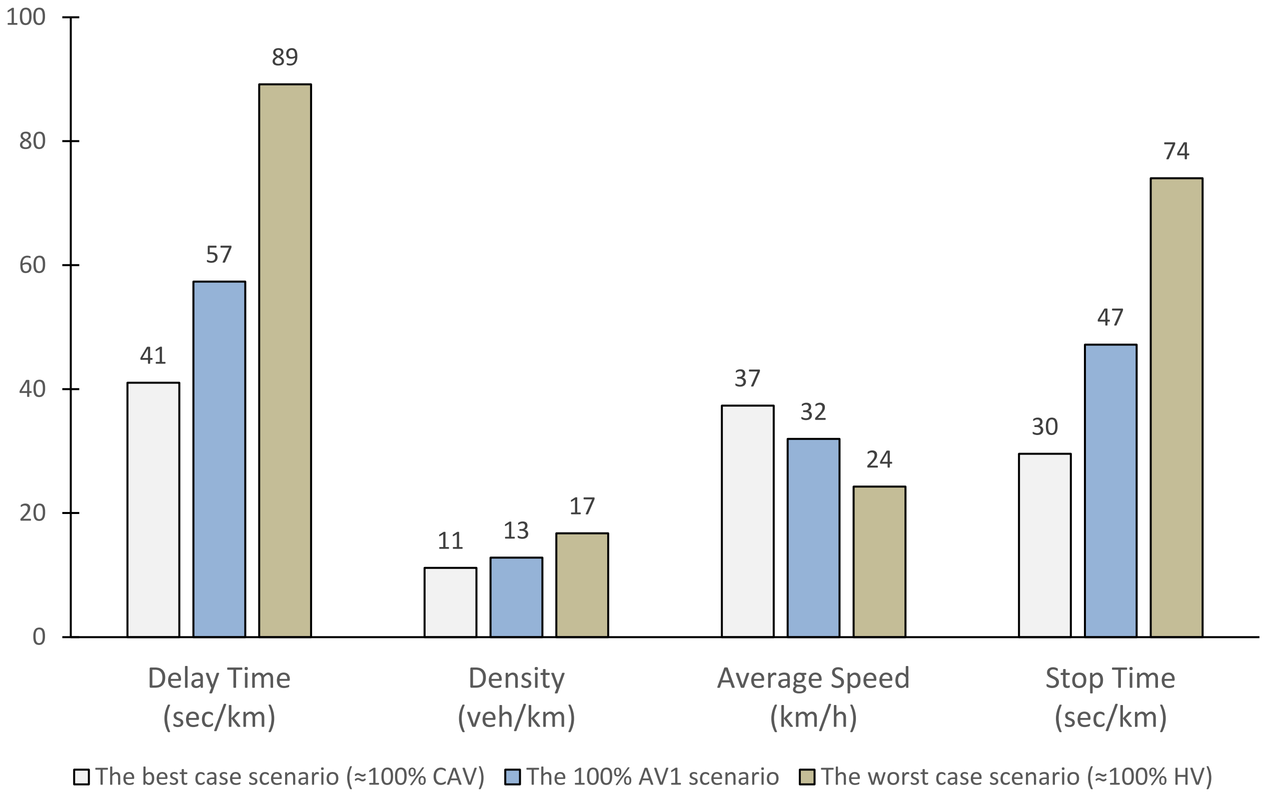

Figure 7: Performance comparison of different scenarios (Canning Highway, 6:45 – 9:45am)

Similar to the freeway results, time series data displayed in Figures 7 to 9 saw 100% CAV simulations generate much smoother and tighter ranged spread of results ranging across the simulation period relative to 100% HDVs.

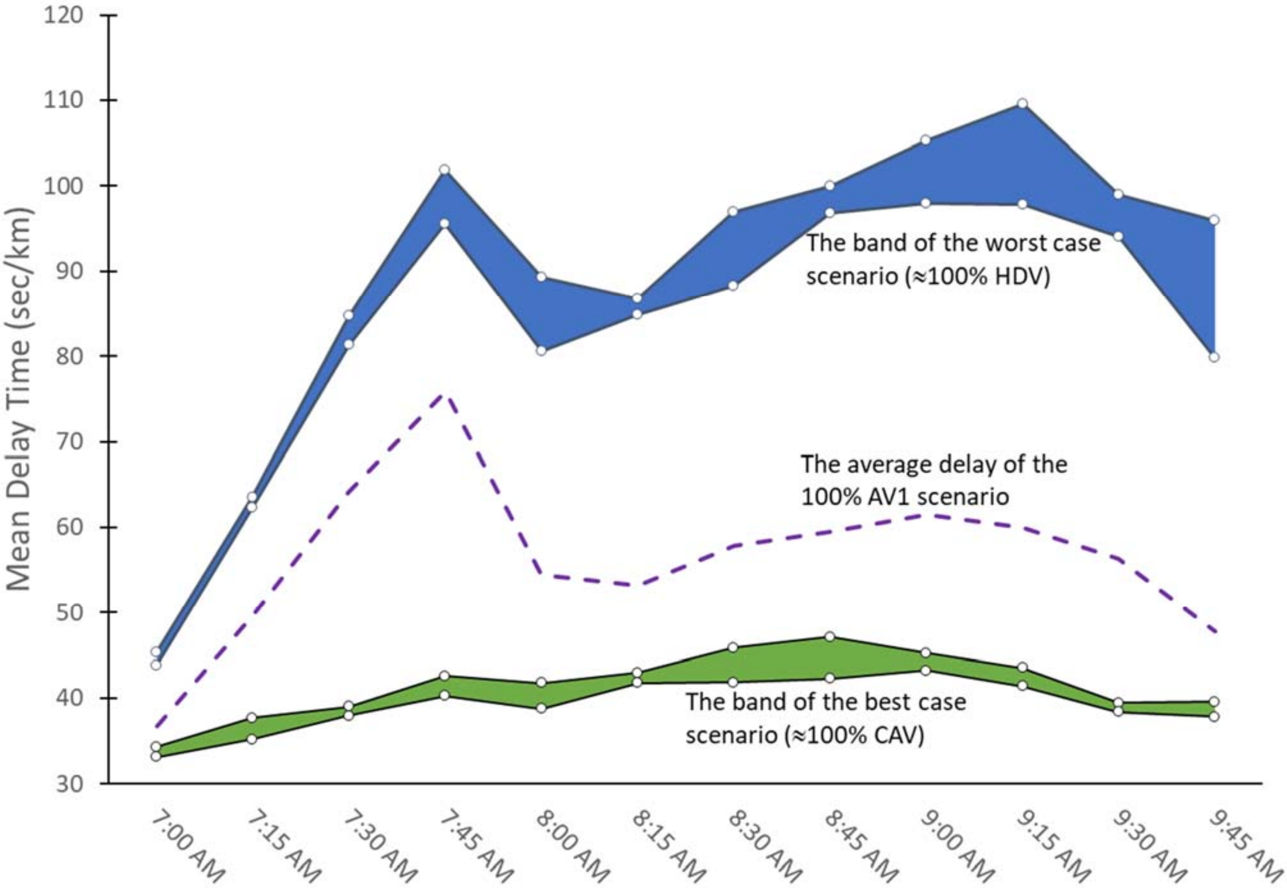

Figure 8: Time series of mean delay time for different scenarios (Canning Highway, AM)

Note: as in Figure 4. AV2 was not included since it was not designed for arterials.

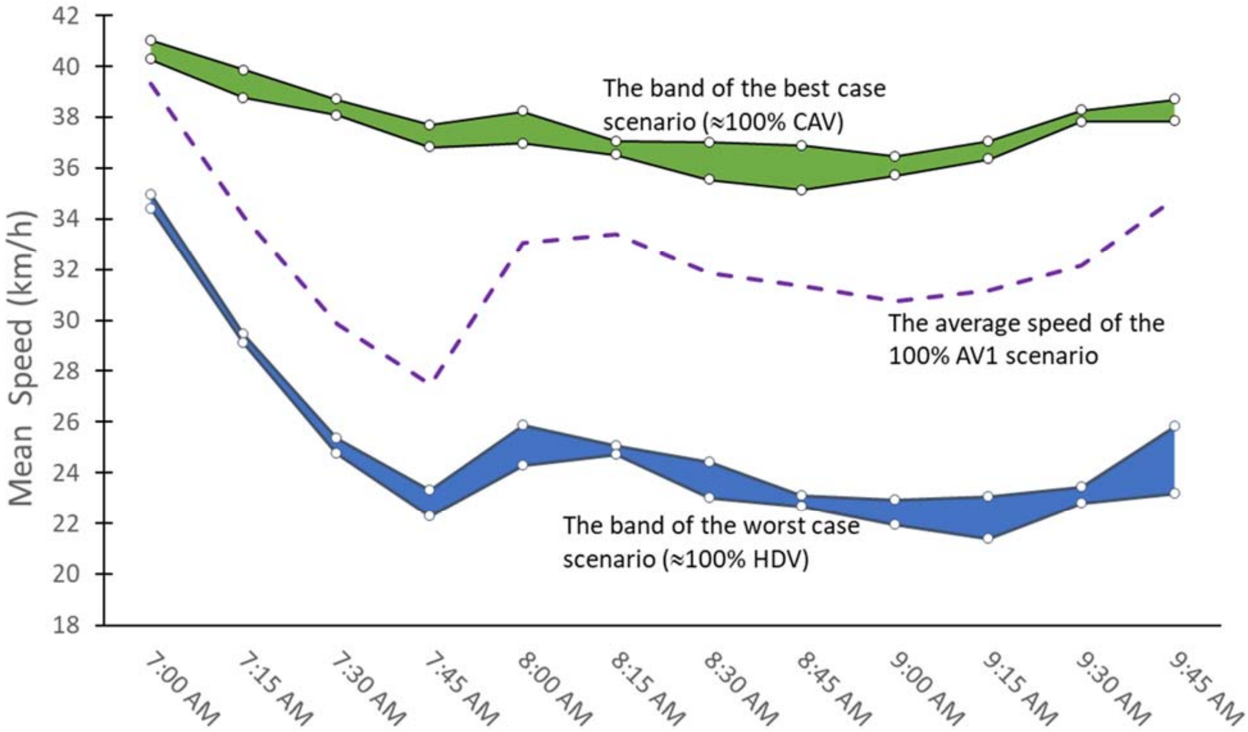

Figure 9: Time series of mean speed for different scenarios (Canning Highway, AM)

Note: as in Figure 4. AV2 was not included since it is not designed for arterials.

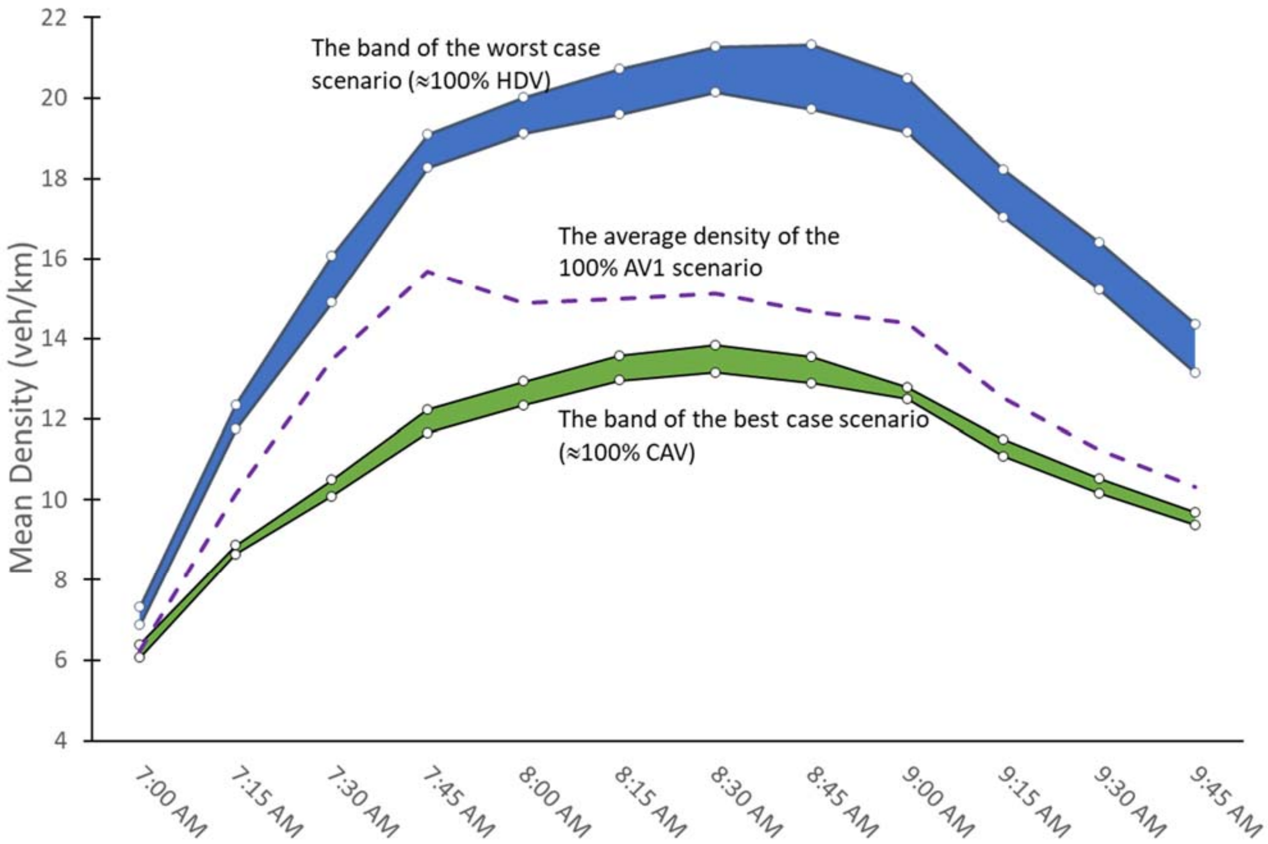

Figure 10: Time series of mean density for different scenarios (Canning Highway, AM)

Note: as in Figure 4. AV2 was not included since it is not designed for arterials.

In general, CAVs and AVs seem to benefit freeways more than arterials. This is because the freeway traffic entirely depends on vehicle interactions so improvement on vehicular technology will have a larger impact. Delays on arterials are caused by both the ‘control devices’ such as traffic signals as well as the level of traffic. The modelled CAVs and AVs improve intersection throughput by simply reacting faster to green lights without the capability of interacting with the lights. More research is needed to investigate how much, more sophisticated V2I technology, can further improve the throughput.

3.3 SIGNIFICANT FACTORS

All the freeway and arterial experiments have revealed several common significant factors that are likely to affect AV and CAV implementation.

3.3.1 REACTION TIME

The system performance is largely determined by those microscopic parameters described in Section 2.2 and the Appendix because they prescribe how vehicles interact with each other and the infrastructure. However, the consequences of changing these parameters are not predictable without the simulation experiments since the number of interactions is enormous and some of them have ripple effects.

Reaction time is one of the most important determining factors among them. Although reaction times at individual vehicle level might seem inconsequential, with HDV average reaction time being 0.9 seconds (Table 5, Appendix), their cumulative effect is probably the most significant among all modelled parameters. Both AVs and CAVs benefited from low or zero reaction times. The estimated parameter ranges are our best estimates based on literature search. However, if the actual vehicle performance is outside of these ranges, the conclusions could be different. For example, if for any reason, AVs have reaction times equal to that of average humans, e.g. manufacturers decide to make their AVs more 'cautious', the model produced longer delays than 100% HDVs. This is also partially because AVs were given a wider range of mechanical parameters (e.g. acceleration and deceleration rates) in the simulations to account for possibilities such as humans deliberately slowing down their vehicles for comfort so their chances of having worse-off combinations increased.

3.3.2 MARKET PENETRATION

The best case is dominated by CAVs because they have zero reaction times. However, they are likely to require a minimum market share to have a visible impact since the technology will only work when both leading and following vehicles are CAVs (Section 2.2, Appendix).

To isolate the impact of connectedness, IDM's mechanical parameters were set to be the same as CAV's.

Additional experiments were conducted for Canning Highway to provide an indication of the impact of market penetration on performance for both AV1 and CAV (Table 3). The results show that increasing AV1 and CAV market shares both reduce the average delay time compared to the base case of 100% HDVs, with CAV outperforming AV1 at every level.

Each scenario considers replacing human driven vehicles with either AV1 or CAV. The three-way mix of HDVs, AV1s and CAVs was not done because it was not clear how to determine the relative share between AV1s and CAVs when they substitute HDVs. For instance, if HDV has 80% market share, the rest is unlikely to be an even split of 10% AV1s and 10% CAVs because CAVs should lag behind AV1s in terms of update due to the extra (e.g. technological and regulatory) requirements and expense that comes with connectivity. Future research could investigate the possibility of synthesising expert predictions to incorporate the joined uptake of both AVs and CAVs in the scenarios and even their relative timeline.

Table 3 Average delay time (sec/km) for different HDV & CAV mix (Canning Highway, 6:45 – 9:45am)

	100% HDV		80% HDV		60% HDV		40% HDV		20% HDV		0% HDV	
	0% AV1	0% CAV	20% AV1	20% CAV	40% AV1	40% CAV	60% AV1	60% CAV	80% AV1	80% CAV	100% AV1	100% CAV
Average Delay Time (sec/km)	86		78	76	72	65	66	56	61	47	56	40
Relative reduction in average delay time	N/A		10%	12%	17%	25%	23%	35%	29%	46%	35%	54%

In Table 3, CAVs at 60% market penetration can deliver almost the same performance as AV1s at 100% market penetration since both achieved 56 sec/km average delay for the simulation period. This is confirmed by the time series chart in Figure 11 by the significant overlap between the two lines. For freeways, it would take even lower percentage of CAVs to match the performance of 100% AVs, since CAVs benefit freeways more than arterials (as shown in Section 3.1 and 3.2).

Figure 11 also reveals that only the 100% CAV scenario achieved a flat delay time curve, meaning it avoided any significant spike altogether and the traffic conditions stayed almost constant throughout the entire simulation period. By comparison, other scenarios all produce a significant peak delay time at the 7:45am mark, as highlighted by the shaded area. It further signifies CAV's advantage over AV. Additionally, although the 80% CAV scenario has a reasonably close average performance to the 100% CAV scenario (Table 3), the gap is still significant at 7:45am when demand reaches a certain level. Therefore, the last 20% connectivity is important in realising the full potential of CAVs. As noted in Figure 11 that CAVs and AV1s were assigned the parameters that gave them near optimal performance so their delay time estimates serve as the lower bound of possibilities and are probably overly optimistic. The relative difference between AV1 and CAV scenarios is arguably more meaningful.

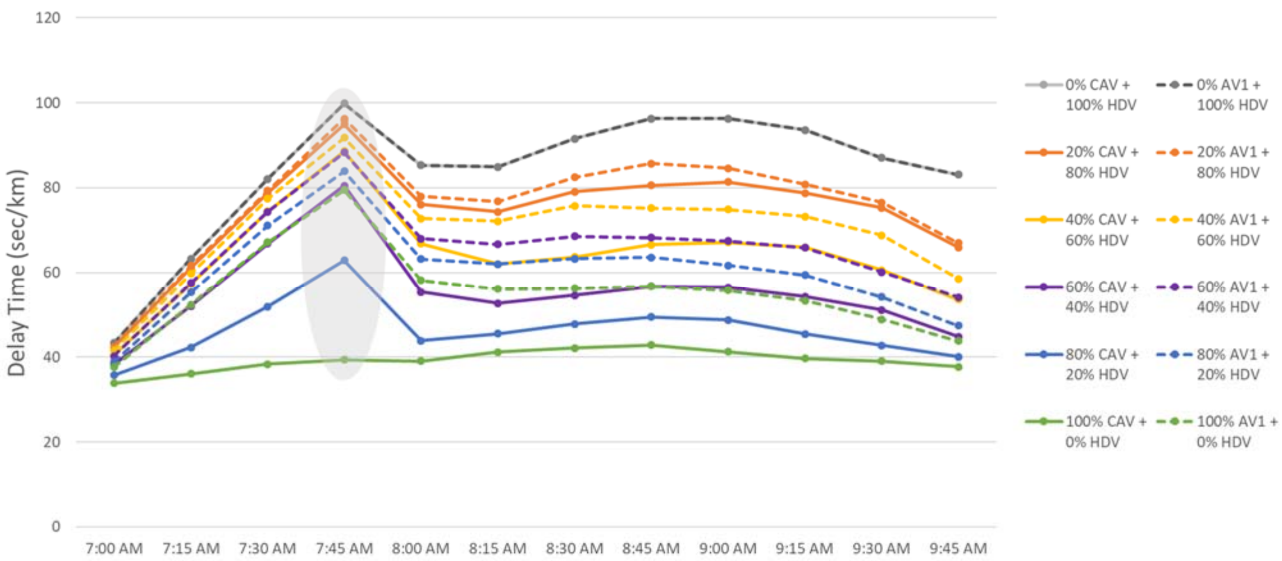

Figure 11 Time series of mean delay time for different HDV, AV1 & CAV mix (Canning Highway, AM)

Note: each scenario in

Table 3 and Figure 11 was averaged across five experiments. The CAV parameters were based on the experiments that produced the best performance in Section 3.2. AV1 parameters were set to match those of CAV's whenever applicable.

3.3.3 UNINTENDED INTERACTIONS BETWEEN CAVS

An entire queue comprising CAVs can move forward together as soon as it is time to go so vehicles joining the back of the queue after lights turn green need not stop. The synchronised movement generates high performance but the closely packed platoon also creates difficulties in lane changing, as shown in Figure 12. This calls for truly cooperative CAV driving algorithms that can coordinate both longitudinal and lateral movements.

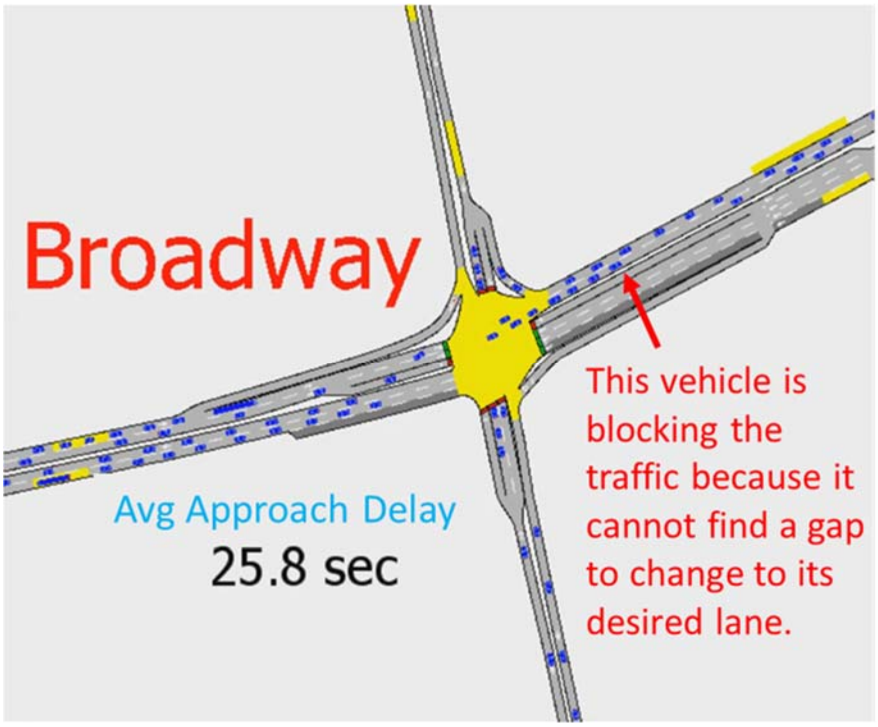

Figure 12 An example of how high vehicle density caused by 100% CAVs can lead to problems in lane changing (Stirling Highway at the Broadway Intersection)

4 DEMAND SENSITIVITY ANALYSIS

This project mostly focuses on the supply side changes, i.e., how much would AVs and CAVs change the road capacity. However, changes to the demand side including human factors are arguably more important because they are less predictable, and the consequences are far-reaching. For example, some people might choose to extend their CAV's car-following distance and consequently lower network performance because they do not feel comfortable travelling too closely behind another vehicle. Fully automated vehicles are also expected to induce demand since they lower travel time costs by enabling passengers to make better use of their in-vehicle time. The current mobility restricted population could also have the new-found freedom to travel independently. Although these could have positive social and economic benefits, the induced demand will at least partially offset the potential capacity increase. Wider implications such as the potential of worsening urban sprawl also need to be carefully assessed. Extensions to the research should thus include demand-side considerations.

Demand modelling with so many uncertainties will require another full-scale study, which is beyond the limited scope of this project. Instead of estimating what is likely to happen, we conducted a sensitivity analysis to test how much extra demand that 100% AVs and CAVs could cope with, while maintaining similar average delay times to the current 100% HDV scenario. The extra demand could be induced by the introduction of AVs and CAVs or simply part of the natural growth.

Table 4 The amount of additional demand that 100% CAV and 100% AV1 can each accommodate while maintaining similar delay times to the current 100% HDV case

	100% CAV		100% AV1	
	Mitchell Fwy	Canning Hwy	Mitchell Fwy	Canning Hwy
Demand increase	80%	50%	5%	15%

Note: Given the stochastic nature of the simulation, the exact match of delay times is not possible, nor is it appropriate. Therefore, the demand increases reported here are rounded to the nearest 5%.

Table 4 shows that 100% CAVs could accommodate much more additional demand than 100% AV1s could, which is expected and again highlights CAVs' advantage over AVs. However, it is surprising that 100% AV1s can only handle 5% additional demand for Mitchell Freeway, although it has achieved over 70% reduction in delay time at the original demand level (Figure 3). It also shows the non-linear relationship between traffic demand and performance, i.e., it does not take a 1% increase in demand to cancel out a 1% reduction in delay time. The freeways are more sensitive to vehicle behaviour changes than arterials because the traffic condition largely depends on how vehicles interact with each other in uninterrupted flows.

5 CONCLUSIONS AND FUTURE RESEARCH

This project modelled the impact of AVs and CAVs on the performance of three Perth roads - Mitchell Freeway, Stirling Highway and Canning Highway. An optimisation algorithm was used to find the best- and worst-case scenarios with shortest and longest travel time delays. AVs and CAVs were given a wider range of parameters to account for the larger uncertainties associated with them. Despite this, all AV and CAV scenarios performed better at 100% market penetration rate compared to the base case comprising 100% HDVs. Freeway results showed greater performance improvement than arterials. The findings imply increased road capacity when AVs and CAVs are prevalent but the disproportionate increase between freeways and arterials could cause a mismatch between their performance which could cause bottlenecks at places where they connect (i.e. ramps).

Among all simulated variables, reaction time appears to be the most significant factor in determining a vehicle's traffic impact. This explains the better performance of both CAV and AVs despite being given a wider range of performance parameters than HDVs. CAVs are by far the winner in all aspects and dominated the best-case scenarios. It is largely due to their zero reaction time in the simulations. At total market penetration, they not only dramatically improved all traffic metrics but also improved travel time reliability, leading to more predictable journey times. Although our literature search suggests that AVs have shorter reaction times than human drivers, if for any reason that is not the case they could perform worse than HDVs, especially if their mechanical performance such as acceleration is also intentionally lowered for reasons such as passenger comfort. Similarly, CAVs' performance could also be comprised by its human users.

The simulations have also revealed some unexpected consequences resulting from vehicle interactions. They highlight the importance of adequately considering the human factors so that AVs are not taken advantage of, and call for truly cooperative CAVs that can coordinate both longitudinal and lateral movements.

The best-case scenario is probably an overestimate but the potential performance improvement of AVs and CAVs does mean certain road capacity expansion might be avoided or delayed. It is advised that the technology readiness for AVs/CAVs should be regularly assessed and business cases should consider them when mass deployment is within reach. We have chosen three AV/CAV driving models from the current literature. However, they might not remain as the best choices as technology advances and our understanding improves. This report should also be updated when new data or information about AV and CAV driving behaviour is available.

The impact of different market shares of HDV with AV1s and HDV with CAVs has been tested. Canning Highway results suggest that for arterials, CAVs at 60% market penetration can delivery almost the same performance as AV1s at 100% market penetration. The percentage is likely to be even lower for freeways. Out of all scenarios, only CAVs at 100% market share achieved a flat delay time curve throughout the simulation period, meaning that it could avoid the peak entirely, although it is the best-case scenario since CAVs (and AV1s) were assigned the parameters that gave them near optimal performance. The relative difference between AV1 and CAV scenarios is arguably more meaningful. Future research could investigate the possibility of synthesising expert predictions to incorporate the joined uptake of both AVs and CAVs in the scenarios and even their relative timeline.

Our demand sensitivity analysis has shown that 100% CAVs can probably handle an increased demand of about 80% on Mitchell Freeway and 50% on Canning Highway while still maintaining similar delay times that are currently produced by 100% HDVs. By comparison, 100% AV1s could only accommodate 5% and 15% additional demand respectively. This further highlights CAVs' advantage over AVs.

Future research should involve more comprehensive modelling of demand changes including the land use and transport feedback loop but it will require a fully calibrated LUTI (Land Use and Transport Interaction) model for Perth, preferably agent-based.

Comparing V2I, V2V as a consumer technology has the advantage of not requiring expensive public infrastructure and its associated maintained costs. Since our results show that V2V plus some simple V2I technologies alone could make significant improvement to the network, further research needs to examine whether this diminishes the necessity of more sophisticated and expensive V2I technologies. Another possible extension of the research is simulating the operations of dedicated AV lanes on Perth's freeways.

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APPENDIX: DRIVING MODELS AND MODEL PARAMETERS

There are different types of models presented in the literature which are used to simulate vehicle behaviour. The main type used to predict vehicle movement is known as a car-following model. These models controls how a vehicle follows the one in front of it depending on the two vehicles' speeds, separating distance, and in some models, acceleration.

In this research HDVs were simulated by Aimsun's default driving behaviour model, a modified version of the Gipps (1981) model that was formulated to model human driver behaviours. *The three existing Main Roads models all run 100% Gipps model to simulate HDVs and they serve as the base cases that reflect the current situation.*

Car-following models alone, however, are not sufficient to simulate vehicle behaviour in complex road environments with traffic signals, give way signs, stop signs and other obstacles. Therefore, for the purposes of this research, the AV and CAV car-following models were supplemented with other Aimsun driving models (such as lane-changing and route planning).

Three car-following models were used based on previously documented research, two for AVs and one for CAVs.

INTELLIGENT DRIVER MODEL (IDM) – REFERRED TO AS AV1

The IDM was initially developed by Treiber, Hennecke & Helibing (2000) and has more recently been repurposed for use in modelling vehicles equipped with adaptive cruise control (ACC). Since then its use has been extended as a model for the behaviour of AVs.

ACC technology has been on the market for a while. The system automatically controls the vehicle's longitudinal motion to maintain a safe distance from the vehicle directly ahead of it while achieving the desired speed when it is safe to do so. Vehicles equipped with ACC are considered as low-level AVs in the SAE standard classification so it is reasonable to use one of the ACC controllers to represent future AVs in terms of the longitudinal aspect of driving.

We use the Improved Intelligent Driver Model (IIDM) because it solves some problems of the original model and produces more realistic results (Treiber and Kesting 2013). It was used to simulate standalone AVs in all three models (Canning Highway, Stirling Highway and Mitchell Freeway).

FOLLOWERSTOPPER MODEL (FSM) – REFERRED TO AS AV2

The FSM is a special AV driving algorithm developed by Stern et al. (2018) for dissipating stop-and-go shockwaves in traffic. They have demonstrated in an experiment that it only took one AV to dissolve the shockwaves produced by the other 20 vehicles. However, the experiment was conducted in an idealistic situation with a single lane ring road, meaning no lane changing was possible. Concerned about this limitation, we created a FSM in Aimsun and reproduced similar results to that of Stern et al. (Cummins 2018). The simulation was then extended to a larger ring with two lanes. It was shown that when lane changing is allowed, human drivers might take advantage of the large gap that the FS vehicle needs for its dissipating strategy, causing it to further pullback and set off a chain reaction to upstream traffic. Stop-and-go waves had thus not been dissipated and decreased traffic performance in terms of flow, speed and delay time occurred.

The purpose of incorporating the FSM in this project was to test whether the same effect would occur in the more realistic freeway environment. Although this did not happen to the Mitchell Freeway model, probably because of the absence of interaction between HV and AV (FSM) and various other factors such as road geometry and vehicle density, it highlights the importance of managing the transition period and adequately considering the human factors. The high-density flow of CAVs has also created difficulties in lane changing in some occasions.

FSM was only applied to the Mitchell Freeway model since its wave dissipating strategy is more suited to freeways and is unlikely to have much effect on arterials.

THE COOPERATIVE ADAPTIVE CRUISE CONTROL MODEL (CACCM) – REFERRED TO AS CAV

The CACCM developed by Van Arem et al. (2006) was chosen to model CAVs. It is an extension of ACC's driving behaviour by adding V2V communication to allow reduced time gap and better coordination between vehicles. It is essentially a CAV car following model for the longitudinal movement.

Although many parameters are included in the HV, AV and CAV driving models, the selected few to be varied and attuned to fit the vehicle driving type are:

- **Reaction time (s):** The time it takes a vehicle to react to speed changes of its lead vehicle.
- **Reaction time at stop (s):** The time it takes a stopped vehicle to react to the acceleration of the lead vehicle.
- **Reaction time at traffic light (s):** The time it takes the first stopped vehicle at a traffic light to react when turning green.
- **Max acceleration (m/s2):** The maximum acceleration of the vehicle.
- **Normal deceleration (m/s^2):** The maximum deceleration of the vehicle under normal conditions.
- **Max deceleration (m/s^2):** The maximum deceleration of the vehicle under emergency braking conditions.
- **Clearance (m):** The distance a vehicle leaves between its front bumper and the rear bumper of its lead vehicle when stopped; sometimes referred to as the 'Jam distance'.
- **Max give-way time (s):** A parameter used in the lane-changing model to adjust the aggressive level of vehicles when in give way situations (e.g. stop signs, give way signs, at on ramps on a freeway etc.). When a vehicle giving way has reached the set Max give-way time, the acceptance margins which vehicles have are reduced to accept smaller

gaps. This parameter is also used as the time a vehicle waits at a standstill before giving up on its desired turn.

- **Speed acceptance:** This parameter denotes the vehicle's degree of acceptance to speed limits on a road section and is implemented as a dimensionless factor. A value of 1 ensures the vehicles max speed corresponds to the set speed limit of the road. When above 1 the vehicles max speed exceeds the speed limit, whereas below 1 restricts its max speed lower than the speed limit.

Table 5 shows key parameter values for different driving models. HV values are taken from Main Roads existing models and AV/CAV values were synthetised from the literature with judgements of the project team (more detail in the following paragraphs). The complete list of parameters including those for the freeways and other vehicle types (trucks and buses) can be supplied to interested readers upon request.

Table 5 Key performance parameter values for different driving models (arterials and cars only)

Parameter	HDVs	AVs	CAVs
Reaction time (s)	0.9	0.1 – 0.5*	0
Reaction time at stop (s)	1.2	0.1 – 0.5	0
Reaction time at traffic light (s)	1.35	0.1 – 0.5	0
Speed acceptance	0.94*	1	1
Clearance (m)	1.85*	1.3 – 2.4*	1.3 – 2.4*
Max give-way time (s)	15*	10 – 30*	10 – 30*
Max acceleration (m/s^2) for arterials	2.7*	1.2 – 3.8*	1.2 – 3.8*
Normal deceleration (m/s^2) for arterials	-3.5*	-3.8 – -1.2*	-3.8 – -1.2*
Max deceleration (m/s^2) for arterials	-6*	-5.5 – -4.5*	-5.5 – -4.5*

*NOTE: values marked with * are drawn from normal distributions and the numbers supplied are their means. Other parameters such as standard deviation, minimum and maximum are omitted to avoid cluttering.*