Effects on Traffic Performance Due to Heterogeneity of Automated Vehicles on Motorways: A Microscopic Simulation Study

Ivan Postigo[1,2][a], Johan Olstam[1,2][b] and Clas Rydergren[2][c]

[1] *Swedish National Road and Transport Research Institute (VTI), Linköping, Sweden*

[2] *Department of Science and Technology, Linköping University, Norrköping, Sweden*

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Abstract: The introduction of automated vehicles (AVs) is commonly expected to improve different aspects of transportation. A long transition period is expected until AVs become prevalent on roads. During this period, different types of AVs with different driving logics will coexist along human driven vehicles. Using microscopic traffic simulation, this study investigates the range of potential impacts on traffic performance in terms of throughput and travel delays for different types of AVs and human driven vehicles on motorways. The simulation experiment includes scenarios with combinations of three different driving logics for AVs together with human driven vehicles at increasing penetration rates. The utilized AV driving logics represent the evolution of AVs, they were defined in the microscopic simulation tool Vissim and were created by modifying and extending the human driver behaviour models. The results of the simulation experiment show a decrease in vehicle throughput and significant effects on delay times when AVs with a more cautious driving logic are predominant. Overall, results show higher vehicle throughput and lower travel delays as AVs evolve to more advanced driving logics.

1 INTRODUCTION

The introduction of automated vehicles (AVs) is commonly expected to improve different aspects of transportation; reduce operational costs, improve safety, ease congestion, decrease energy usage, increase driving comfort, among others. From a traffic performance perspective, AVs are usually expected to improve traffic by being able to keep smaller gaps between vehicles, by always complying with road regulations, and by smaller variations compared to human drivers both in the way they drive as well as on how they react to their surroundings.

In order for AVs to be allowed in public roads, they need to be proven safe. This requirement would lead first generations of AVs to focus on minimizing risks, and to drive more cautiously than most human drivers.

Road authorities are interested on how the deployment of AVs will affect traffic conditions, in order to avoid possible negative impacts and to take advantage of possible benefits. Motorways arguably present less challenging conditions for automated driving to be first introduced, mainly due to the one-directional traffic flow and separation from pedestrians and non-motorized transport modes (ERTRAC, 2019). On motorways, AVs would primarily have to deal with the interaction with other vehicles and not with traffic lights, pedestrian crossings, nor would they have to anticipate all potential circumstances of urban scenarios.

To estimate the impact of AVs on motorways, microscopic traffic simulation is a suitable tool since the movements of all vehicles and the interaction between them are simulated. However, models used in simulation tools were originally developed to describe human driving behaviors, thus, in order to used them for automated driving, the models require modifications, extensions or replacement with new models. Suggestions for approaches on how to extend current models exist, but while large scale field data remains unavailable to validate them, any approach will include large uncertainties.

The presence of AVs is expected to gradually increase over the next decades (Calvert et al., 2017; Milakis et al., 2017; Tillema et al., 2017; Litman, 2015).

[a] https://orcid.org/0000-0002-4745-4865
[b] https://orcid.org/0000-0002-0336-6943
[c] https://orcid.org/0000-0001-6405-5914

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During this transition period, public acceptance and AV-related technologies will evolve, allowing following generations of AVs to gradually have less conservative driving styles. It is reasonable to expect that different generations of AVs, with different capabilities and driving styles, will be present on roads alongside human driven vehicles.

This study aims to investigate the range of potential impacts on motorway traffic performance caused by the simultaneous presence of different types of AVs and human driven vehicles. This coexistence is expected during the transition to a predominant presence of AVs. The impact on traffic performance is measured in terms of vehicle throughput and travel delays.

A simulation experiment using the microscopic traffic simulator Vissim is presented. The simulation experiment includes multiple scenarios, with increasing market penetration rates of AVs and with different mixes of three driving logics within the AV share. The three AV driving logics represent different generations of AVs and the evolution of their driving capabilities. They were developed within the H2020 CoEXist project (Coexist, 2020) and are implemented in Vissim (Sukennik, 2018b).

The remaining of this article is structured as follows. Section 2 presents a background on which this study is base and limitations of microscopic models for modeling automated driving. The simulation experiment is described in Section 3, a description of the simulated motorway segment, a conceptual description of the different driving logics used for AVs and details of the included scenarios. Section 4 presents the results and the impact of AVs on traffic performance in terms of change in capacity by measuring throughput and travel delays. Finally, Section 5 ends the article with conclusions and need for future research.

2 BACKGROUND

Some commercially available vehicles are currently implemented with advanced driving assistance systems like adaptive cruise control (ACC) or lane centering systems which automate the driving experience to a certain degree. Top global automakers claim to have fully automated driving vehicles available for consumers by the early 2020s. However, current available automated driving systems are not yet capable of operating fully autonomously.

The society of automotive engineers (SAE), which develops standards for various transport industries, proposes six levels to describe driving automation (SAE, 2018). SAE levels 0 to 2 describe driver support features that assist drivers to different extents but require the driver to steer, brake or accelerate as needed to maintain safety. The more advanced levels (SAE levels 3 to 5) describe automated driving features, from optional automated driving under specific conditions to full automated driving on any condition.

First generations of AVs (SAE level 3) are expected to have automated driving as an option under specific conditions with the driver still responsible for the driving. While first SAE level 3-4 vehicles could be expected by early 2020s, some studies give a time estimation of decades until AVs become a considerable share of the vehicles and automated driving becomes the norm.

In (Tillema et al., 2017) the penetration rate of AVs is estimated by the different levels of automation, taking around 15 years for AVs to have perceptible effects on traffic flows and up to 50 years for AVs to be a prevalent presence on roads. In (Milakis et al., 2017) the transition path to a prevalent presence of AVs depends on different factors from local governmental policies to technology development. While the path remains unclear, (Milakis et al., 2017) sets horizons for the years 2030 and 2050 for transport implications in the Netherlands caused by the wider deployment of AVs. In (Calvert et al., 2017), based on different sources, it is estimated that it will take at least 15 years until 20% of the vehicles become automated. Based on patterns it took previous vehicle technologies to be deployed, cost of the technology and sales projections, (Litman, 2015) estimates a period of three to five decades until the majority of trips are made by AVs. (Litman, 2015) presents estimations from 2013, and predict a small number of AVs by the time this study is presented (2020). However, most advanced commercially available vehicles are not yet capable of fully automated driving though there are claims from vehicle manufacturers that it is just around the corner. Overall, it is estimated that it is a matter of decades until AVs become predominant in roads.

Different traffic simulation studies aiming to investigate the impacts caused by AVs can be found in the literature. Effects caused by different vehicle technologies on different road environments have been investigated. The impact of AVs on urban environments has been investigated (Lu et al., 2019), in which AVs were modelled by modifying parameters in the car following model. Analysis on the effects of ACC and cooperative adaptive cruise control (CACC) are commonly found in the literature (Liu et al., 2018; Yuan et al., 2009; Arem et al., 2007; Minderhoud and Bovy, 1999), but analysis are limited to longitudinal control of the ACC or CACC and not to vehicles capable of overtaking or lane changes. The impact of AVs in merging roadways is investigated in (Rios-Torres and Malikopoulos, 2017). The influence of AVs on flow stability and throughput is studied in (Talebpour and Mahmassani, 2016). The studies have shown that AVs will affect traffic flows in different ways, both improving or degrading traffic performance. Usually, it is assumed that all AVs will drive according to the same driving logic (e.g. (Olia et al., 2018)), and their impacts are commonly estimated by including scenarios with increasing market penetration rates of AVs. Moreover, the approaches taken to model AVs or automated driving in simulation investigations vary from study to study.

Microscopic simulation models have been developed aiming to describe human driving behavior. To model the driving logic of AVs, these models need to be modified, extended or replaced. Modifying parameters of existing car following models or lane changing models is a fast and simple approach to model AV driving logics. This could for example be modifications on distances kept between vehicles, reaction times, accepted distances for lane changing, acceleration and speed parameters. If a specific feature of AVs can not be modeled by changing parameter values, then the models could be extended or replaced. New or extended models could aim to simulate vehicles sensors, control algorithms or safety features.

Nonetheless, regardless of the approach taken to model AVs, the calibration of the models is based on the available data, which currently is limited to existing partly automated vehicles, and not based on future automated driving. Therefore, investigations based on traffic simulation of AVs should consider a range of possible driving logics for AVs (e.g (Olstam et al., 2020; Mintsis et al., 2019)).

3 EXPERIMENT SETUP

The purpose of the simulation experiment done in this study is to enhance the understanding of potential impacts caused by AVs. The simulation experiment has been delimited to a motorway environment due to the less challenging conditions they present for first automated driving systems to consider them within their operational design domain. The results present the range of effects on traffic performance caused by different AV mixes, showing the impact of the coexistence of different types of AVs alongside human driven vehicles.

The uncertainties related to the transition to full vehicle automation and to the evolution of the capabilities of AVs are addressed by including multiple scenarios in the simulation experiment. The transition period to full vehicle automation is considered by creating scenarios with increasing penetration rates of AVs, that is, the proportion of AVs present in the traffic flow. This represents the expected gradual increase in the of number of AVs present in roads. Three AV driving logics are used to represent the evolution of AVs. These driving logics assume different levels of cautiousness in their driving styles, recognizing that as the technology that allows automated driving advances, AVs will become more reliable in regards to safety. However, the uncertainty does not relate only on how the technologies will evolve but also on how fast they will be implemented in vehicles. Thus, scenarios with all possible combinations of the three AV driving logics are included, each combination is a specific AV mix. They represent both a faster and a slower evolution of AVs as well as the coexistence of different types of AVs. The results obtained regarding the effects caused by this coexistence are the main contribution of this simulation experiment.

The simulation experiment is conducted for a German representative motorway stretch (Sonnleitner, 2018). The AVs in the simulation are assumed to have perfect knowledge of the geometry of the motorway. Some elements of the motorway, like the position of lanes or traffic signs, are perceived in reality through sensors on the vehicle, which is assumed to be perfect in the simulation. As seen in Table 1, AVs with different driving logics interact with different number of vehicles or objects. The accuracy, latency and reliability of the perception of other vehicles or objects depend on whether the perception is done through on board sensors or through connectivity features. This perception is assumed to be perfect in the simulation and with zero latency, and how it is accomplished is implicitly included in the driving logics.

Future motorways might support automated driving by including digital infrastructure which will provide static and dynamic information to the AVs. The infrastructure support for automated driving (ISAD) (Carreras et al., 2018) considered in the simulation experiment is ISAD-level D or E, which corresponds to a conventional infrastructure with little support for automated driving. The vehicles in the simulation perceive different number of leading or trailing vehicles, as well as immediate vehicles in target lanes for lane changing maneuvers, they don't have additional information about the traffic conditions elsewhere along their routes. Since there is no support from the infrastructure included in the motorway model, all dynamic driving tasks are handled by the driving logics.

3.1 Modeling of Automated Vehicles

The three driving logics used to model AVs are called: *cautious, normal* and *all-knowing*. These driving logics were developed within the H2020 CoEXist project (Coexist, 2020) and are implemented in Vissim. They are not exact driving algorithms, instead they represent different levels of cautiousness based on the possible behaviour of AVs and how they would resolve conflicts, e.g. reaction times, gap thresholds, etc (Sukennik, 2018b). The logics are based on the Wiedemann 99 car following model (PTV, 2020) with adjusted parameters.

The *cautious* driving logic is the most conservative and aims to ensure not only that AVs don't cause any accidents, but also to establish confidence on the public about the safe operation of AVs. This forces the vehicle to adopt larger distances to surrounding vehicles. An *enforced absolute braking distance* feature is enabled (see Table 4). The absolute braking distance is the distance a vehicle must keep in order to brake safely and avoid a collision if a vehicle in front comes to a sudden full stop. The calculation of the absolute braking distance considers a vehicle's own speed, braking capacity and relative position to the vehicle in front, it neglects the leading vehicle's speed and braking capacity, as it assumes that the vehicle in front could suddenly "turn into a brick wall". This distance is also required for the lane change maneuver, which means that it will have less chance of taking place, the distance must exist both to the leading and trailing vehicles in the target lane.

The *normal* driving logic was developed with the intention of being similar to human drivers. In contrast to human driven vehicles however, AVs with this driving logic are capable of shorter reaction times and have more accurate measurements of distances to other vehicles as well as relative speeds. They are restricted by the range of their sensors to only perceive vehicles in their proximity and surroundings, unlike human drivers who are often aware of vehicles beyond their proximity.

The *all-knowing* driving logic intends to model the most advanced AVs capable of keeping smaller gaps for all maneuvers and also have shorter reaction times. AVs with this driving logic are assumed to be connected to the infrastructure and thus receive information about vehicles and objects beyond their surroundings. This connectivity feature is implicitly included in this driving logic, as shown in Table 1, *all-knowing* AVs interact with 10 objects and 8 vehicles, compared to only 2 objects and 1 vehicles for the AVs with the other driving logics.

All implicit stochastics have been disabled for all AVs, which makes them show less variations on their driving compared to human drivers. Human driven vehicles are modeled with a desired speed distribution which allows them to travel at a much wider range of speeds, even surpassing the speed limits. On their side, AVs always comply with the specified speed limits and are modeled with a desired speed distribution with a range of only ± 2 km/h from the speed limit. The acceleration and deceleration functions are also different for AVs, showing less variation than human driven vehicles. The values of the used parameters are presented in Tables 1, 2, 3 and 4.

Table 1 shows the difference in perception modeled for each driving logic. The values show that the *cautious* driving logic has a shorter range for perception. And, as previously mentioned, only the more advanced *all-knowing* driving logic is able to perceive several more vehicles and objects. In Table 2, the exact parameter values used for the Wiedemann 99 car following model (PTV, 2020) are presented as they appear in Vissim. These values show the difference on cautiousness or aggressiveness between the driving logics. Table 3 shows the values for the parameters used to perform necessary lane changes. They show that acceleration and deceleration is more restricted in the *cautious* driving logic, as well as the required distances to perform the maneuver. Lastly, Table 4 shows the additional functionalities of Vissim used for each driving logic. All values are based on the recommendations from (Sukennik, 2018a) and (Olstam et al., 2020).

3.2 Scenarios Setup

Figure 1 shows the model of the motorway used in the simulation experiment. It is a two lane motorway going in one direction from point A to point C with a speed limit of 130 km/h, covering 1 km in length. The model includes an off-ramp with one lane with a length of 200 m, and a similar on-ramp. A 'warm-up' section of 1 km in length was included before point A which is not shown in the Figure. The main flow of vehicles will enter the network through point A. A secondary flow, entering the network through point B is set to be 25% of the number of vehicles generated for the main flow. Lastly, the number of vehicles taking the off-ramp is 20% of the number of vehicles passing through point A.

The heterogeneity of AV that may exist in future motorways was included by creating different AV mixes. Each unique AV mix, where each AV driving logic has 0, 20, 40, 60 or 80 or 100% share of the total number of AVs were created, leading to 21 possible combinations. Three of these unique mixes contain a

Table 1: Driving behaviour parameters for following in Vissim.

	Driving Logic			
	Cautious	Normal	All-knowing	Human Driven
Look ahead distance				
Minimum (m)	0	0	0	0
Maximum (m)	150	250	300	250
Number of interaction objects	2	2	10	2
Number of interaction vehicles	1	1	8	99
Look back distance				
Minimum (m)	0	0	0	0
Maximum (m)	150	150	150	150

Table 2: Driving behaviour parameters for car following model in Vissim.

	Driving Logic			
Wiedemann 99 model	Cautious	Normal	All-knowing	Human Driven
CC0 - stanstill distance (m)	1.5	1.5	1.0	1.5
CC1 - headway time (s)	1.5	0.9	0.7	1.05
CC2 - 'following' variation (m)	0.0	0.0	0.0	4.0
CC3 - threshold for entering 'following' (s)	-10.0	-8.0	-6.0	-8.0
CC4 - negative 'following' threshold (m/s)	-0.1	-0.1	-0.1	-0.3
CC5 - positive 'following' threshold (m/s)	0.1	0.1	0.1	0.35
CC6 - speed dependency of oscillation (10^{-4}rad/s)	0.0	0.0	0.0	11.44
CC7 - oscillation acceleration (m/s^2)	0.1	0.1	0.1	0.25
CC8 - standstill acceleration (m/s^2)	3.0	3.5	4.0	3.5
CC9 - acceleration with 80 km/h (m/s^2)	1.2	1.5	2.0	1.5

Table 3: Driving behaviour parameters for lane change in Vissim.

	Driving Logic			
	Cautious	Normal	All-knowing	Human Driven
Maximum deceleration (m/s^2)				
Own	-3.5	-4.0	-4.0	-4.0
Trailing vehicle	-2.5	-3.0	-4.0	-3.0
-1 m/s^2 per distance (m)				
Own	80	100	100	300
Trailing vehicle	80	100	100	200
Accepted deceleration (m/s^2)				
Own	-1.0	-1.0	-1.0	-1.0
Trailing vehicle	-1.0	-1.0	-1.5	-0.75
Minimum headway (front/rear) (m)	1.0	0.5	0.5	0.5
Safety distance reduction factor	1.0	0.6	0.75	0.6
Maximum deceleration for cooperative breaking (m/s^2)	-2.5	-3.0	-6.0	-3.0

Table 4: Driving behaviour functionalities in Vissim.

Functionality	Driving Logic			
	Cautious	Normal	All-knowing	Human Driven
Enforce absolute braking distance	On	Off	Off	Off
Advanced merging	On	On	On	On
Cooperative lane change	Off	On	On	On

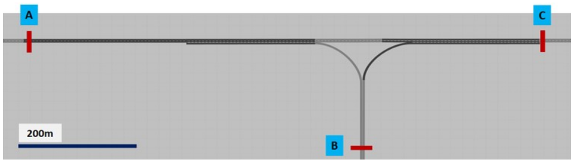

Figure 1: Motorway model. Flows are generated at points A and B.

single type of AV. Twelve mixes contain two types of AV, with one type being 60 or 80% the total number of AVs. The remaining 6 mixes include all three types of AVs, where each type is 40 or 60% the total number of AVs.

The gradual increase of AVs in roads is considered by including six different AV penetration rates of 0, 20, 40, 60, 80 and 100%. At 0% penetration rate there are only human driven vehicles, while at 100% penetration rate, there are only AVs on the network.

Seven different demand levels for the main flow of 1000, 2000, 3000, 4000, 5000, 6000 and 7000 vehicles per hour (veh/h) were generated before point A. For the secondary flow, generated at point B, the corresponding demands are 250, 500, 750, 1000, 1500 and 1750 veh/h.

Each scenario consists of a specific combination of demand level, AV penetration rate and AV mix, giving a total of 742 scenarios, seven of which don't include any AVs (0% penetration rate). A simulation time of one hour plus 30 minutes of 'warm up' time until the network reached a stable state was run for each scenario. The results for are based on 10 replications with varying random seeds.

Additional scenarios were added to see the impact of the *enforced absolute braking distance* feature in the *cautious* driving logic. The feature was disabled and the results compared to the scenarios with a single AV driving logic.

4 RESULTS AND ANALYSIS

The results of the simulation experiment are presented in terms of vehicle throughput and travel delay. The lines shown in the figures are color-coded for each AV mix, the legend shows thick solid lines indicating the AV mixes that include a single type of AV. The colors used are cyan for *cautious* AVs, orange for *normal* AVs, green for *all-knowing* AVs and gray for human driven vehicles. The remaining 18 lines are not shown in the legend to avoid cluttering. The color of each line represents the type of AV is most present in the mix, while the color of the marker represents the second most present type of AV. The line is shown without a maker if there is an equal share between the remaining two types of AVs. The 95% confidence interval shadows each line in Figures 5 to 8.

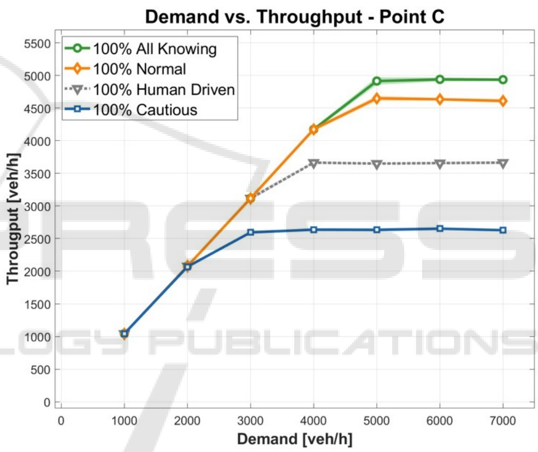

Figure 2: Throughput measured at point C for different demands levels generated on the main flow at point A for scenarios with a single type of vehicle.

Figure 2 shows the measured throughput at point C. The Figure shows that each case reaches a maximum throughput at different demand levels. The highest vehicle throughput occurs for the 100% *all-knowing* AV mix, almost doubling the maximum throughput measured for the 100% *cautious* AV mix. Every scenario reaches a maximum throughput when demands on the main flow are higher than 5000 veh/h. Thus, the effects on vehicle throughput caused by the different AV mixes at different penetration rates are more interesting for scenarios with high demands. The results presented in Figure 3 correspond to a demand on the main flow of 6000 veh/h. Figure 3 shows that the highest vehicle throughput always occurs for the '100% *all-knowing*' AV mix, while the lowest vehicle throughput occurs for the '100% *cautious*' AV mix. The measured throughput of every

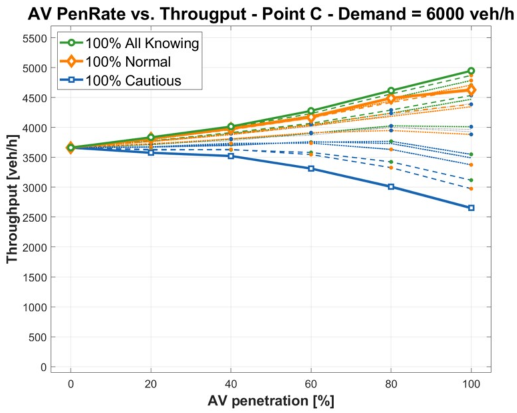

Figure 3: Throughput measured at point C for all 21 AV mixes at different AV penetration rates for a demand on the main flow of 6000 veh/h.

other AV mix is found within this range. By closer inspection of each AV mix, the throughput increases when the *normal*, and *all-knowing* driving logics are more present in the flow. Similarly, when more AVs with the *cautious* driving logic are present, the measured vehicle throughput decreases even compared to the case when there are only human driven vehicles (i.e. 0% AV penetration rate).

Back in Figure 2, it is shown that in the absence of AVs (100% human driven vehicles), the maximum vehicle throughput is observed when the demand on the main flow is above 4000 veh/h. Figure 4 shows the measured throughput for a lower demand of 3000 veh/h. At this lower demand, effects on vehicle throughput is noticed only at high AV penetration rates, and occurs for the AV mixes composed by mostly or by only *cautious* AVs. Though little impact occurs on vehicle throughput, Figures 5 and 6 show more noticeable impacts on average travel delays even at lower demands, both on the main flow, as well as on the secondary flow.

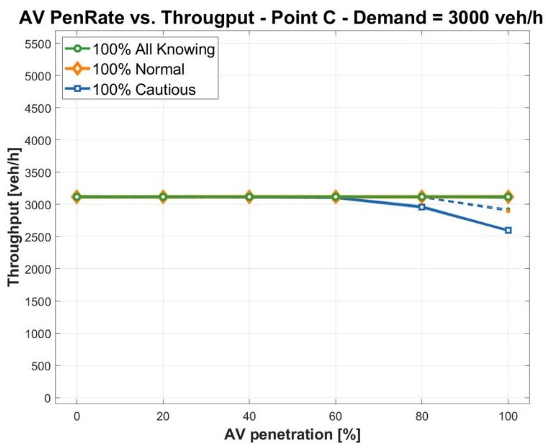

Figure 4: Throughput measured at point C for all 21 AV mixes at different AV penetration rates for a demand on the main flow of 3000 veh/h. The lines are mostly overlapping.

Figures 5 and 6 show results in terms of average travel delays for vehicles travelling from point A to C (the main flow) and from point B to point C (the secondary flow) respectively. Different demand levels for scenarios with a single type of vehicle, i.e. only human driven vehicles and only each type of AV are presented. The Figures show that compared to the main flow, the secondary flow shows higher delays for the AV mix of 100% *cautious* as demand increases. The larger gaps required by *cautious* AVs might be preventing them to merge into the main flow, causing the larger increase on delays seen on the secondary flow.

A more detailed investigation on queue formation would be required to understand the large in-

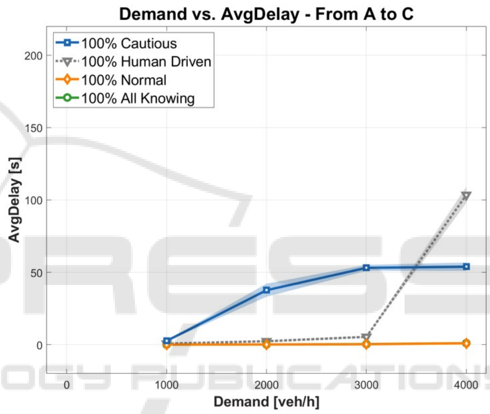

Figure 5: Average travel delays for vehicles going from point A to point C for different demands levels generated on the main flow at point A for scenarios with a single type of driving logic.

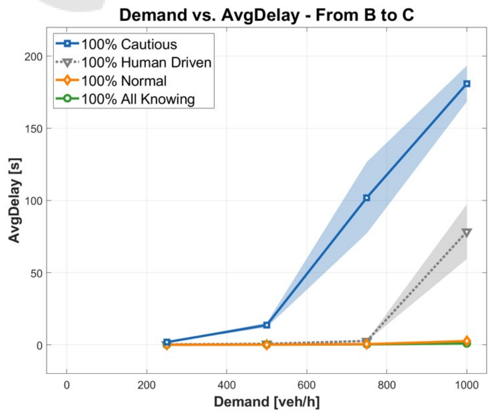

Figure 6: Average travel delays for vehicles going from point B to point C for different demands levels generated on the secondary flow at point B for scenarios with a single type of driving logic.

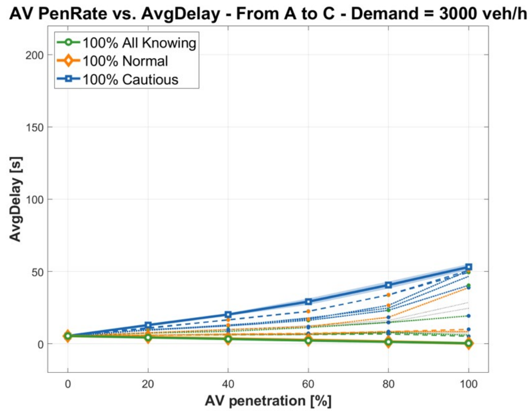

Figure 7: Average travel delays for vehicles going from point A to point C for all 21 AV mixes at different AV penetration rates for a demand on the main flow of 3000 veh/h.

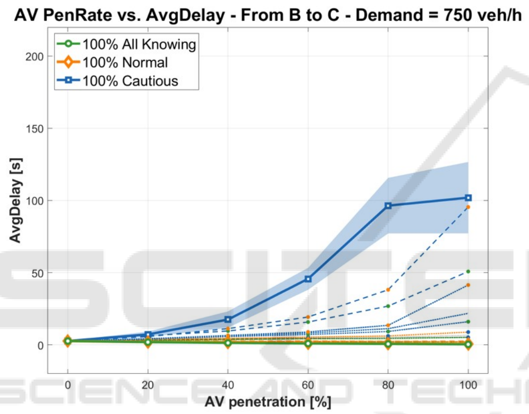

Figure 8: Average travel delays for vehicles going from point B to point C for all 21 AV mixes at different AV penetration rates for a demand on the secondary flow of 750 veh/h.

crease in delays seen in the secondary flow as demand increases for the AV mix of 100% *cautious*. Based on observations, our hypothesis is that once the main flow reaches its maximum throughput demands higher than 2000 veh/h, the required absolute braking distance prevents most *cautious* AVs coming from the secondary flow to merge into the main flow. Similarly, if a *cautious* AVs comes from the left lane on the main flow, it might experience problems to switch to the right lane to reach the off ramp if its route is to leave the motorway. This could explain the observed flattening on the average delay curve of the main flow (A to C) for the AV mix of 100% *cautious* as demand increases, shown in Figure 5, as well as the rapid increase of average delays for the same AV mix on the secondary flow (B to C), shown in Figure 6.

Figures 7 and 8 show the impact of average travel delays for a demand of 3000 veh/h on the main flow

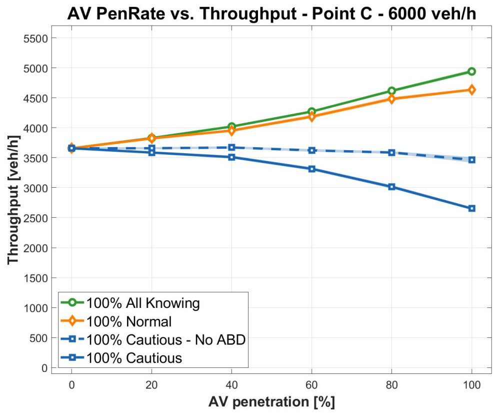

Figure 9: Throughput measured at point C for AV mixes with a single AV logic at different AV penetration rates for a demand on the main flow of 6000 veh/h. An additional AV *cautious* driving logic with the *enforced absolute braking distance* feature disabled is included.

(A to C, Figure 7) and a corresponding demand of 750 veh/h on the secondary flow (B to C, Figure 8) for different AV penetration rates and for all AV mixes. Similar to the vehicle throughput, the minimum and maximum average travel delays occur for the AV mixes of 100% *cautious* and 100% *all-knowing*. The observed travel delays of every other AV mix are found within this range. The average travel delays are higher when the more cautious AVs are more present in the flow.

The results obtained for the *cautious* driving logic could relate to the *enforced absolute braking distance* feature. To investigate the impact the feature has in terms of vehicle throughput scenarios were run with the *enforced absolute braking distance* feature disabled, the results are shown in Figure 9. Even though the measured throughput still decreases as the AV penetration rate increases, the decrease is not as large as when the feature is enabled.

The results obtained for the different mixes of AVs show that effects are intuitive, meaning that the higher share of less cautious AVs (i.e *normal* and *all-knowing* driving logics), the higher throughput and the lower average travel delays. Only as the share of more cautious AVs increases (i.e *cautious* driving logic), there is a decrease in measured vehicle throughput and an increase in average travel delays.

Lastly, the results show that impacts on vehicle throughput are noticeable only at high demands, while effects on travel delays are noticeable even at lower demands.

5 CONCLUSIONS

The simulation experiment shows that as automated driving moves away from cautious driving styles, or in other words, as the capabilities of AVs allow them to keep shorter gaps and have faster reaction times, an increase in the capacity of motorways can be expected. In the same way, if automated driving does not evolve and stay as the *cautious* driving logic, capacity on motorways could decrease. Moreover, while the effect on vehicle throughput is unnoticeable at lower demands, the effect on average travel delays are noticeable at lower demands.

The results for scenarios with heterogeneous AV mixes are within the ranges of AV mixes with a single type of AVs. Thus, the conclusion is that there are no unexpected effects caused by the interaction between the different AVs types.

A desirable road-map for the introduction of AV can be drawn from the results obtained, knowing that an automated driving style as the *cautious* driving logic could have negative impacts and that an evolution on the driving style of AVs should be encouraged.

The results found from the scenarios with a large share of *cautions* AVs indicate that a deeper understanding of what occurs in the merging zones is needed. Moreover, since first AVs will most likely keep large gaps as the *cautious* driving logic, a deeper investigation is needed on how to prevent the disruption of the traffic flow that this *cautious* driving logic is causing.

Disabling the *enforced absolute braking distance* in the *cautious* driving logic shows that the high safety requirements that the feature has is preventing vehicles to merge and might be *over* cautious. Though we don't know the exact details on how the feature is implemented in Vissim, a *relative braking distance* feature would be more flexible, and might accomplish the same safety requirements without being *over* cautious.

The simulations assumed AVs to have a perfect perception, not affected by inaccuracies or latency introduced by sensors or connectivity features. Moreover, the infrastructure considered corresponds to ISAD-Levels D and E, which provides little support for automated driving. Changes in the modeling of perception and/or including digital support from the infrastructure might allow to change the modeling approach of automated driving, causing to observe different effects in the traffic flow due to the presence of AVs.

It is debated how the presence of AVs will affect the driving behavior of human drivers (HF Auto, 2017). This discussion has been left out of the scope of this study and the assumption made was that the driving behavior of human driven vehicles will not change. Future investigations could include changes on driving behavior of human drivers caused by the presence of AVs.

The focus of this study has been the effects of AVs on motorways using Vissim. Further research could focus on other road environments, using different microscopic simulators with different approaches on how to model automated driving.

Finally, vehicle throughput and average travel delays, show larger differences in results between the *cautious* and *normal* driving logics than between the *normal* and *all-knowing* driving logics. This might indicate that there is a large benefit of evolving from the *cautious* to the *normal* driving logic. If AVs are not expected to have such a big leap in their driving styles, an additional driving logic representing an intermediate evolution stage should be included in future investigations.

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