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Impact of Automated Highway Autopilot on the Performance and Safety of Weaving Sections

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Abstract

Allowing level 4 Automated Vehicles to drive on highways could significantly impact the traffic efficiency and safety. Although it might probably take a while before AVs are on the road, NRAs (National Road Authorities) are already investigating how to adapt their current infrastructure to make it ready for AVs – while optimizing both traffic efficiency and safety. Therefore, in this paper we simulate a highway section in VISSIM including a weaving section calibrated with empirical data. We test different taper lane lengths, different demand levels (0.55 and 0.80 F/C ratios) and different CAV penetration rates (0-100%) and we assess the impact on traffic efficiency and safety. It is concluded that increasing AV penetration rates lead to decreasing travel times for all road users (automated and non-automated). Different taper lane lengths as well as different traffic flow levels do not seem to influence the observed pattern much.

Keywords: autonomous vehicles; highway autopilot; VISSIM; weaving section; NRA

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Acronyms

ACC	Adaptive Cruise Control
AV	Automated Vehicle
CACC	Cooperative Adaptive Cruise Control
CAV	Connected Automated Vehicle
CEDR	Conference of European Directors of Roads
CV	Conventional Vehicle
F/C	Flow/Capacity ratio
KPI	Key performance indicator
NRA	National Road Authority

1. Introduction

The research presented in this paper is the result of initial work done in the scope of the MANTRA project MANTRA which is an acronym for "Making full use of Automation for National Transport and Road Authorities – NRA Core Business". This is a project that responds to the question posed by CEDR Automation Call 2017 Topic A: How will automation change the core business of NRA's? In this paper we focus on the impact of highway autopilot on the traffic efficiency and safety and on what could NRA's expect if they allow Automated Vehicles (AVs) on the roads in terms of traffic efficiency (e.g., road capacity, average travel time) and traffic safety (e.g., speed variability). Can they already prepare themselves by for example varying lengths of taper lanes of on-ramps, off-ramps, weaving sections to reduce negative impacts on traffic efficiency and safety?

1.1. Highway autopilot

According to ERTRAC (2017), the highway autopilot, including highway convoy, provides automated driving up to 130 km/h on highways, or similar roads to highways, from the entrance to exit, on all lanes, including overtaking and lane change. The driver must deliberately activate the system, but does not have to monitor the system constantly. The driver can at non-critical times override or switch off the system. There are no requests from the system to the driver to take over when the system is in normal operation area (i.e. on the highway). Depending on the deployment of cooperative systems, ad-hoc convoys could also be created if Vehicle-to-Vehicle communication is available.

1.2. Impact mechanisms and relevant key performance indicators

The variety of impacts and impacts mechanisms of connected and automated driving, and the related key performance indicators (KPIs) regarding connected automated driving impacts were comprehensively defined by the Trilateral WG and CARTRE group (Rämä and Kuisma, 2018). These include mobility and travel behavior, driver behavior, traffic flow, traffic safety, user acceptance, energy, and environment. For the MANTRA research, we have selected the most relevant KPIs. The following sub-sections present the main findings of the review of the literature on the selected KPIs based on Deliverable 3.1 of the MANTRA project.

The selection of the KPIs were based on the importance of the KPIs to road operators and their relevance for the traffic simulation analysis in this research. Namely, we have selected those KPIs that could be assessed with mico-simulation, or could be useful as input to the micro-simulation study.

1.2.1. Driving speed & speed variability

In AVs, the longitudinal driving behavior is mainly determined by the ACC or CACC systems. Different studies have reached contradicting conclusions regarding the impact of ACC on driving speeds, but rather consistent conclusions with respect to the speed variation. In the EuroFOT study (Kessler et al., 2012) the Adaptive Cruise Control (ACC) was evaluated in a bundle with the Forward Collision Warning (FCW). A significant increase in the average driving speeds on highways was found when using the ACC in combination with FCW systems. A follow-up simulation study (Kessler et al., 2012) found that the effect on network speed is similar in size to the effect found in the FOT and has a linear trend with higher penetration levels. The simulations were based on the driving behavior and system usage observed in the FOT. Aria et al. (2016) who used VISSIM found an increase of 8.48% in the average speed on the autobahn segment in the p.m. peak hour in the 100% automated vehicles

scenario compared to the 100% conventional vehicles scenario. It was also shown that there is less dispersion around the mean speed in accordance with the findings of previous studies (Viti et al., 2008).

1.2.2. Time headway

In AVs, the time-headway is based on the ACC (highway autopilot) or CACC (highway autopilot + convoy) settings, which are never lower than the legally prescribed value. Therefore, it is expected that the time-headways will be larger than those adopted by human drivers who often drive with time-headways lower than the legally prescribed value (Alkim et al., 2007). This has indeed been shown in the EuroFOT study (Kessler et al., 2012). An increase in the average time-headway of about 16% on highways was found when using the ACC. Similar results were found in a naturalistic driving study with ACC-equipped vehicles in different traffic states on highways (Schakel, Gorter, de Winter, & van Arem, 2017). Larger headways are expected to reduce traffic flow capacity, while the reduction in the fluctuation of the headway, can reduce events of breakdown, which are inevitable with human driving, and eventually lead to an increase in capacity. On the other hand, automation in combination with Vehicle-to-Vehicle communication offers the possibility of platooning with shorter time headways between vehicles, which can increase the traffic capacity of lanes and thus traffic efficiency (Ntousakis, Nikolos, & Papageorgiou, 2015). Objective measurements in the study by Nowakowski et al. (2011) show that drivers of the CACC system selected vehicle-following gaps that were approximately half the length of the gaps they selected when driving the ACC system.

1.2.3. Capacity

The capacity of a road is highly related to the time headway. As was shown in the previous section (*1.2.2*), users of ACC tend to keep a larger headway than manually driven vehicles. In accordance with this finding, Bierstedt et al. (2014) concluded that non-connected autonomous vehicles would indeed degrade highway capacity due to the safety-conscious programming of ACC equipped vehicles. Their simulation suggests that capacity benefits will only occur if 75% of the fleet mix consists of AVs – leading to traffic flow benefits of 25-35%. Friedrich's (2016) findings are identical. Although commonly a human reaction time of 1.8 seconds is assumed, empirical studies showed that headways of manually driven vehicles on highways are significantly shorter, especially at high traffic volumes (Wagner, 2014).

On the other hand, connectivity brings a lot of benefit. Headways decrease, resulting in an increase in capacity on highways. Shladover et al. (2013) studied the impact of connected vehicles for different market penetration rates using microsimulation. They used time gaps as chosen by drivers during a field test with automated vehicles. Increasing market penetration of CACC leads to an increased road capacity – up to 3970 vehicles/hour/lane for a 100% CACC scenario compared to a capacity of 2200 vehicles/hour/lane in the base scenario. When considering ramps and weaving sections, the introduction of connected automated driving might result in a decrease in capacity with small penetration rates (Rämä & Kuisma, 2018). This is due to the discontinuities where lane changes take place (van Beinum et al., 2018). Although homogeneous speeds of drivers result in fewer shockwaves, this results in a higher difficulty of performing lane changes. This might cause vehicles being stuck at merging sections, not able to get to the lane where they want to be. This has been shown for example in the study by Makridis et al. (2018) who showed that AVs result in an increase of congestion due to the inability to predict movements of neighbouring vehicles during lane changes. However, connected autonomous vehicles outperform manual driven vehicles with high penetration rates. Especially during high demand, a large decrease in congestion was observed – identical to the finding of Rios-Torres (2017). With a low penetration rate, there's no vehicle to communicate with, falling back to a non-connected behaviour.

1.2.4. Travel time

It is expected that with the introduction of connected and automated vehicles (highway autopilot + convoy), travel times would reduce. This is because of the possibility of reduced time headway and the communication between vehicles, which increases traffic stability, and reduces shockwaves. For example, Aria et al. (2016) found that there is a reduction of about 9% in the average travel time in the scenario with 100% automated vehicles in comparison to the scenario with the 100% of conventional vehicles in the p.m. peak. Rios-Torres and Malikopoulos (2017) found that 100% CAV penetration rate allowed for a significant reduction in travel time (up to 60%) in moderate and high traffic congestion situations in merging roadways.

2. Methodology

In order to get a first idea of the impacts of highway autopilot on traffic efficiency and safety that NRA's may expect in the future, we simulate a stretch of a highway which includes a weaving section. In the simulation, we also test the impact of different taper lengths. The weaving section includes both an on-ramp and an off-ramp.

2.1. Network set-up

Traffic simulations are performed using microsimulation software VISSIM 11. We model a highway section with 2 lanes and a speed limit of 120 km/h, corresonding to a capacity of about 4200 pcu/hour. The modelled weaving section is of the "Ex-Ex type" according to AASHTO (2018), meaning that the on-ramp and off-ramp are on the same side (i.e. right side) of the road. According to empirical trajectory data collected from a video camera mounted underneath a hovering helicopter above weaving sections in the Netherlands (van Beinum et al., 2018), we assume that merging vehicles (i.e. vehicles that enter the highway) have a speed of 80 km/h, and only start accelerating to the maximum speed limit once they enter the taper lane. In this study, we use the demand data from the Dutch A59 Klaverpolder-north (van Beinum et al., 2018) which entails that 15% of traffic is merging and 7% of traffic is diverging.

2.2. Driving logic

Two types of vehicles are simulated: conventional vehicles (i.e. driven by a human) and automated vehicles (AVs). The conventional vehicles (CVs) are modelled according to the calibrated parameters resulting from empirical trajectory data of 2 weaving sections in the Netherlands (van Beinum et al., 2018). These are different than the default Wiedemann99 car-following model. For example, the time headway is changed from 0.9 seconds (VISSIM) to 0.5 seconds (empirical data according to van Beinum et al., 2018).

For modelling an AV the recommended numerical values as proposed by the CoEXist project (2018) are used. We are interested in the impact of highway autopilots including highway convoy. Therefore, we assume that AVs have a perfect perception and prediction of the traffic situation, including cooperative behavior and connectivity (a CAV). This corresponds to the driving logic class "All knowing" as defined by CoEXist. Main differences compared to the CV are longer time headways (0.6 seconds), an increased desired acceleration (110%) and cooperative lane change functionality. Additionally, the CoEXist project, as well as literature (Viti et al., 2008), assumes that AVs have less dispersion around the mean speed. The desired speed value is therefore set to 118-122 km/h, as opposed to the default of 85-155 km/h.

2.3. Simulation scenarios

We model 11 different penetration rates of AVs (from 0 to 100%, in steps of 10%). Additionally, we simulate two levels of demand: a free flow situation and a near traffic jam situation. This corresponds to Flow/Capacity ratios of 0.55 and 0.80, i.e. a Level of Service of B (reasonably free flow) and D (approaching unstable flow). To assess possible interventions taken by NRAs to increase future traffic flows, we model two different lengths of taper lanes: 300m which is the minimum design length in the Netherlands (Rijkswaterstaat, 2017) and 600m, the minimum design length according to AASHTO (2018).

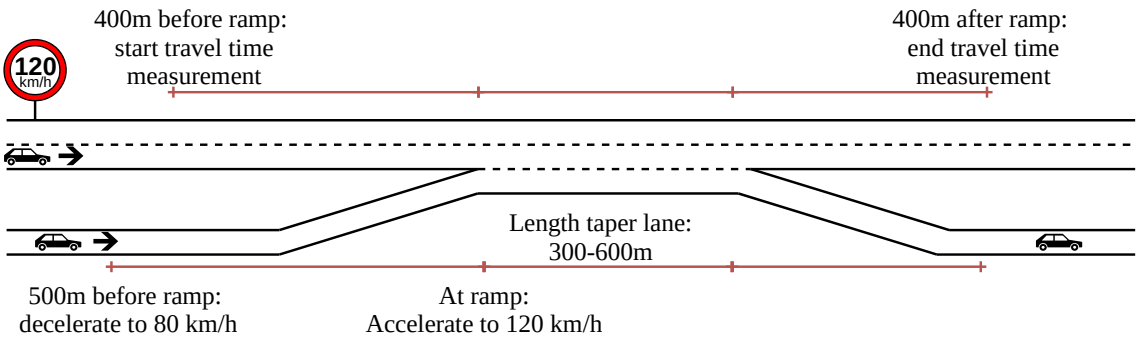

Fig. 1 Overview of simulated weaving section

In total, this implies running 44 different configurations. Every configuration is run 11 times with different random seeds. For every simulation, we record the average travel time of all vehicles (split per vehicle type, AV vs. CV) over a segment between 400m before the on-ramp and 400m after the off-ramp, split in through-going, merging (coming from the on-ramp) and diverging (taking the off-ramp) traffic. The complete overview of the network is shown in Fig 1.

3. Results

Results of average travel times for a weaving section with a 0.55 Flow/Capacity ratio are shown in Fig. 2. It can be seen that in general the average travel times are decreasing as penetration rates increases. Differences between a taper lane with length 300m or 600m are marginal. This corresponds with the empirical findings of van Beinum et al. (2018), who concluded that most of both entering and exiting drivers desire to change lanes in the first part of the weaving segment, leaving the second half unused. Therefore, longer weaving segement lengths seem to have little benefit. Additionally, travel times of AVs and CVs do not differ much from each other.

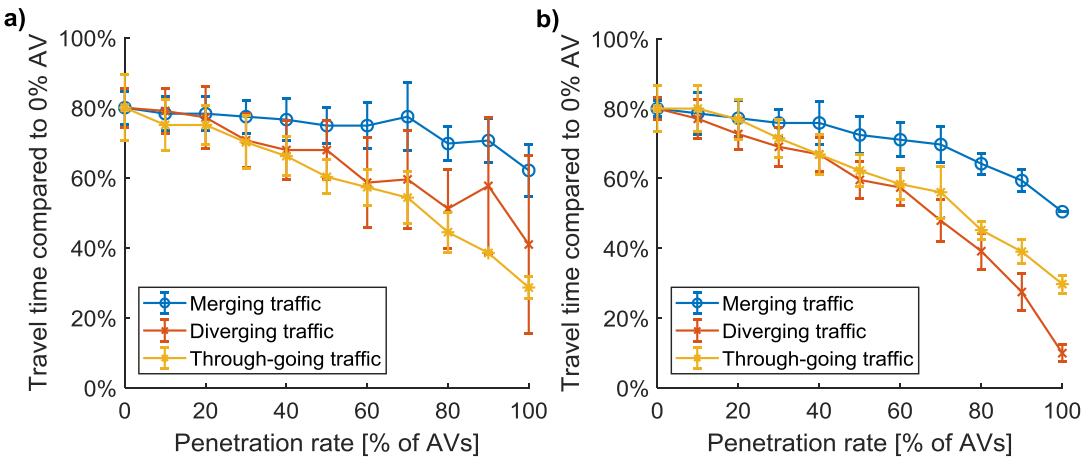

Fig. 2 Average travel times for a weaving section with a 0.55 Flow/Capacity ratio, with a a) 300m or b) 600m taper lane

An increased traffic flow with flow/capacity ratio of 0.80 shows the same pattern (see Fig. 3), with decreasing vehicle travel times as penetration rates increase.

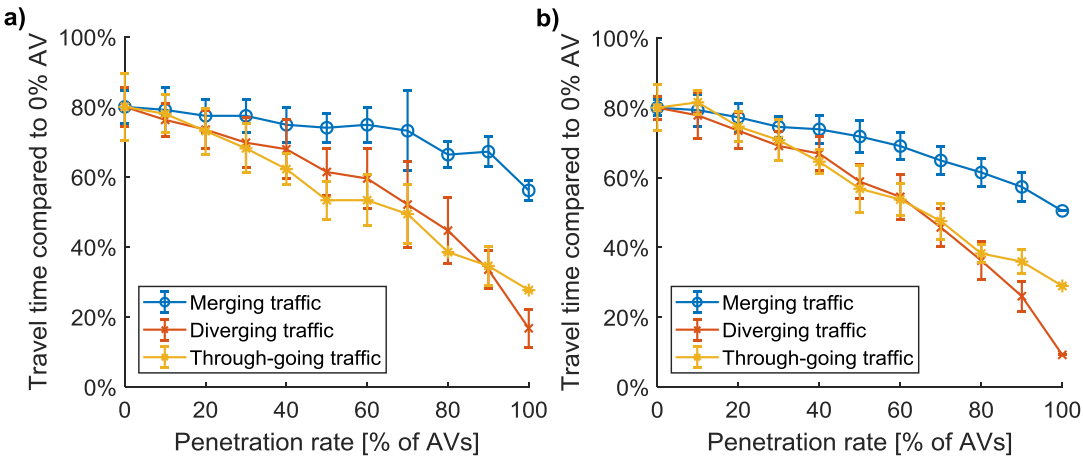

Fig. 3 Average travel times for a weaving section with a 0.80 Flow/Capacity ratio, with a a) 300m or b) 600m taper lane

4. Conclusions

In this paper, we investigated the impacts of highway autopilot including highway convoy and performed numerous simulations with VISSIM. We simulated a weaving section on a highway, with AVs that have the ability to communicate and show cooperative behaviour. Results with different traffic demand levels and taper

lane lengths show that decreasing travel times are to be expected with increasing penetration rates, also at small percentages of AVs. Influences of different taper lane lengths or demand levels seem to be marginal.

Results of microsimulations highly depend on parameter settings. Although the results of different random seeds show equal trends, we did not vary any of the driving behaviour parameters. We used quite aggressive AV-parameter settings, for example including a time headway of only 0.6 seconds. In reality, it is expected that the earliest AVs on the road will have longer headway settings compared to conventional vehicles to ensure safety. This might result in a negative impact by allowing AVs on the highways.

The results that we found do not necessarily correspond to earlier findings in literature (Rämä & Kuisma, 2018), indicating that a decrease in travel time only occur after a certain penetration rate of connected AVs. This is probably caused by using the calibrated parameters of van Beinum et al. (2018) to model conventional vehicles. These settings are quite aggressive compared to the default parameters within VISSIM. For example, the time headway component is set to 0.5 seconds instead of the default value of 0.9 seconds, which might have considerable effect on the results.

In general, NRAs should take notice that AVs on the highway are most likely going to lead to decreased travel times. More research is required on the role of NRAs in decreasing negative impacts of the deployment of highway automation by changing road design guidelines, for example by investigating Infrastructure to Vehicle communication and traffic speed management. Additionally, more research on the impact of AVs around different infrastructure objects (e.g. on-ramps, off-ramps) might be worth researching.

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References

AASHTO, 2018. A Policy on Geometric Design of Highways and Streets.

Alkim, T.P., Bootsma, G., Hoogendoorn, S.P., 2007. Field Operational Test "The Assisted Driver", IEEE Intelligent Vehicles Sysmposium, Istanbul, pp. 1198 - 1203.

Aria, E., Olstam, J., & Schwietering, C., 2016. Investigation of automated vehicle effects on driver's behavior and traffic performance. Transportation Research Procedia, 15, 761-770.

Bierstedt, Jane, Aaron Gooze, Chris Gray, Josh Peterman, Leon Raykin, and Jerry Walters, 2014. Effects of next-generation vehicles on travel demand and highway capacity. FP Think Working Group, 10-11.

CoEXist, 2018. D2.3 Default behavioural parameter sets for Automated Vehicles (AVs).

ERTRAC, 2017. Automated Driving Roadmap. Version 7.0, Date: 29/05/2017. ERTRAC Working Group “Connectivity and Automated Driving“. 54 p. http://www.ertrac.org/uploads/images/ERTRAC_Automated_Driving_2017.pdf

Friedrich, B., 2016. The Effect of Autonomous Vehicles on Traffic. In B. Friedrich, Autonomous Driving (pp. 317-334).

Kessler, C., Etemad, A., Alessendretti, G., Heinig, K., Selpi, B. R., Cserpinszky, A., Benmimoun, M., 2012. European large-scale field operational tests on in-vehicle systems: Deliverable D11. 3. Aachen: euroFOT Consortium.

Makridis, M., Mattas, K., Ciuffo, B., Raposo, M., Toledo, T., & Thiel, C., 2018. Connected and automated vehicles on a freeway scenario. Effect on traffic congestion and network capacity. 7th Transport Research Arena TRA.

Nowakowski, Christopher, Steven E. Shladover, Delphine Cody, Fanping Bu, Jessica O'Connell, John Spring, Susan Dickey, and David Nelson, 2011. Cooperative adaptive cruise control: Testing drivers' choices of following distances. No. UCB-ITS-PRR-2011-01.

Ntousakis, I. A., Nikolos, I. K., & Papageorgiou, M., 2015. On microscopic modelling of adaptive cruise control systems. Transportation Research Procedia, 6, 111-127.

Rämä, P., Kuisma, S., 2018. Societal impacts of automated driving. CARTRE (Coordination of Automated Road Transport Deployment for Europe) deliverable D5.3.

Rios-Torres, J., & Malikopoulos, A. A., 2017. Automated and cooperative vehicle merging at highway on-ramps. IEEE Transactions on Intelligent Transportation Systems, 18(4), 780-789.

Rijkswaterstaat, 2017. Richtlijn Ontwerp Autosnelwegen 2017.

Schakel, W. J., Gorter, C. M., de Winter, J. C., & van Arem, B., 2017. Driving Characteristics and Adaptive Cruise Control? A Naturalistic Driving Study. IEEE Intelligent Transportation Systems Magazine, 9(2), 17-24.

Shladover, S., Su, D., & Lu, X.-Y., 2013. Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow. Transportation Research Record: Journal of the Transportation Research Board, 2324(September 2015), 63-70.

van Beinum, A., Farah, H., Wegman, F., & Hoogendoorn, S., 2018. Driving behaviour at motorway ramps and weaving segments based on empirical trajectory data. Transportation Research Part C: Emerging Technologies, 92, 426-441.

Viti, F., Hoogendoorn, S. P., Alkim, T. P., & Bootsma, G., 2008. Driving behavior interaction with ACC: results from a Field Operational Test in the Netherlands. Paper presented at the 2008 IEEE Intelligent Vehicles Symposium.

Wagner, P., 2014. Traffic control and traffic management in a atransportation system with autonomous vehicles. In: Maurer, M., Gerders, J., Lenz, B., Winner, H., (eds) Autonomous Driving. Springer, Berling, Heidelberg