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Impact of connected and autonomous vehicles on the capacity of signalized intersections – Microsimulation of an intersection in Munich

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Abstract

In recent years, there have been several studies about the impact of connected and automated vehicles (CAVs) on the capacity of street networks. However, most studies consider a purely automated traffic on freeways where neither human drivers nor pedestrians or bicyclists are present. With the introduction of CAVs into the urban road environment, the effect of CAVs on inner-city traffic becomes more and more important. This paper focuses on the impact that an increasing share of CAVs with a harmonized driving behaviour will have on the capacity of signalized urban intersections. We do not only consider the scenario with pure automated traffic, but analyse several scenarios with mixed traffic, where an increasing number of CAVs shares the road with human drivers as well as other road users. The effects are assessed by simulating a representative signalized intersection in central Munich, Germany, using real data considering the geometry of the intersection, the signal control and the traffic volume. Our study shows that average waiting times at the intersection can decrease significantly.

Keywords: Autonomous Vehicles, Microsimulation, Signalized Intersection Capacity, HBS

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1. Introduction

During the last decades, traffic congestion has become a significant problem in large cities. In Munich, for example, drivers need to put up with an increase in travel time of 51% during the morning peak, according to the TomTom Traffic Index (TomTom International BEV, 2017). Traffic problems in cities might become even bigger in the future, as an increasing share of the world's population resides in urban areas – in 2014, 54% of the world's population was urban, whereas by 2050, 66% of the world's population is projected to live in urban areas (United Nations, 2014). This will lead to increased traffic and the urge for innovative ideas. Many people hope for an increase in street and intersection capacity due to the emergence of connected and autonomous vehicles (CAVs). CAVs are expected to be especially beneficial at signalised intersections, where the reorganization of intersection policies, i.e. so-called Autonomous Intersection Management (AIM) strategies show promising results (Chen et al., 2016). However, the AIM strategies introduced in recent studies only work for purely autonomous intersections without any human interaction. This will most likely never be the case for most intersections in urban areas, as bicyclists and pedestrians are an important part of urban road users. Additionally, CAVs will not be implemented all at once, but the vehicle fleet in a city will change continuously over time. Therefore, it is not only interesting to assess how traffic will change when all vehicles are CAVs but also how traffic is influenced if 10, 20, …, 100% of the vehicles driving in a city are CAVs.

Effects of CAVs in mixed traffic have been studied mainly for freeways and inter-urban highways and are expected to be implemented in these fields first. This is due to the fact that in urban traffic, many complex situations arise where vehicles have to interact with so-called vulnerable road users (VRUs), i.e. with pedestrians and bicyclists, in rapidly changing situations. However, introducing CAVs to the urban environment has a great potential, especially when enabling autonomous taxi services. Urban traffic infrastructure is installed for a long period of time and does not change completely with the introduction of the first CAVs. Therefore, CAVs have to cope with the existing infrastructure and human road users, and effects of CAVs on intersections have to be measured assuming existing structures.

In this paper, we analyse the impacts of an increasing share of CAVs on the capacity of a signalized intersection including human driven vehicles, trucks, pedestrians and bicyclists. To this end, we model all road users considering important parameters such as reaction times, and acceleration behaviour. We then calculate the capacity of a real signalized intersection in Munich, Germany and simulate the traffic flow at this intersection including an increasing number of CAVs. For the simulations, we apply the signal control plan that is used at this intersection in reality. We are aware that the results obtained in this study cannot be generalized to findings valid for all intersections, as each intersection has to be investigated separately. However, the change in capacity is an indicator for other intersections as well.

The remainder of the paper is structured as follows: in Chapter 2, we give an overview of related literature considering capacity impacts of CAVs. In Chapter 3, we present the considered intersection in Munich, Germany, including necessary information such as signal programme, layout plan and traffic volume. In Chapter 4, we present results of the capacity calculation using the "Handbuch für die Bemessung von Straßenverkehrsanlagen" (HBS) – the German version of the Highway Capacity Manual – and simulation results. We also explain the assumed parameters for the simulation of the behaviour of both human road users and CAVs used in our study. Finally, we give a conclusion and outlook in Chapter 5.

2. Related Literature

Even though it is not yet clear when CAVs will be available to the public, there is already quite a lot of literature available that estimates the effects that CAVs will have on the capacity of road networks. Most studies either consider mixed traffic on freeways and highways or purely autonomous traffic at intersections.

Krause et al. (2017) analysed the impacts of AVs and CAVs on the capacity of German freeways in different merging situations. They observed an increased capacity only for a share of at least 50% of CAVs, while an increasing share of AVs showed a decrease in capacity due to bigger headways. Van Arem et al. (2006) analyzed the impacts of cooperated adaptive cruise control (CACC) on traffic flow for a highway-merging scenario from four to three lanes. They found out that CACC is able to improve traffic stability and throughput. These benefits appear for a CACC penetration rate of more than 60%, whereas no effect could be shown for low penetration rates of less than 40%.

Lioris et al. (2017) showed that the capacity of an intersection can be doubled due to the forming of platoons. They analyzed the capacity by evaluating a mesoscopic simulation of a sequence of streets and intersections near Los Angeles. However, they did not analyse mixed traffic conditions considering both CAVs and human drivers.

Levin et al. (2016) developed a cell transmission model for shared human and autonomous roads to investigate the impacts of autonomous vehicles on the travel time both on highways and at intersections. They observed a linear reduction in travel time for an increased share of autonomous vehicles. These results have not been verified with simulations or real tests yet.

Independent of autonomous vehicles, the possibility of vehicle to vehicle and vehicle to infrastructure communication shows a high potential for improving traffic efficiency and emission reduction. Several projects on cooperative traffic signal control have been conducted, simultaneously optimizing the traffic signal programme and the speed of the vehicle approaching a traffic light. If the approaching vehicle is not autonomous, the driver is given an optimal speed advisory in order to reach the traffic light during a green light phase (Santa et al., 2014). The coordinated traffic signal timing to provide green waves can also be improved using vehicle to infrastructure communication (Hu, 2016).

Our paper contributes to the current research in that we take “one step back” as compared to other studies. Not only do we consider a mixed traffic flow in most of the scenarios, but we also leave the circumstances encountered at the intersection today unchanged. For example, we do not change the signal control programme of the intersection. Signalised intersections are planned considering all traffic participants. When calculating intergreen times, it is important to take into account the velocity and clearing times of all road users in order to ensure a safe crossing of the intersection for all traffic participants. Obviously, the lowest velocity and hence highest clearing time of all road users are crucial. This means that the clearing times of bicyclists are decisive for the calculation of intergreen times in the signal control plan. This is independent of the proportion of CAVs in the traffic flow. Additionally, we do not consider green light optimal speed advisory or other car-to-infrastructure communication. Car manufacturers aim at building autonomous vehicles that do not rely on infrastructure in order to be able to drive anywhere independent of the infrastructure investments of the respective country or municipality. Additionally, a German ethics commission advising the government in regulatory questions for CAVs warns of missing protection of data privacy (Di Fabio et al., 2017).

We follow the calculations on capacity impacts, considering both freeways and highways as well as signalised intersections given by Friedrich (2016) and Wagner (2016). Friedrich states that intersections are the bottlenecks of urban traffic and, when traffic load is high, waiting queues of traffic do occur independent of the coordination of traffic signals. Therefore, the vehicles start moving from standstill when the traffic light changes to green and the capacity of the intersection is most dependent on reaction times, on the time gap between vehicles, and on the velocity with which they cross the intersection (Friedrich, 2016). Wagner describes the process of approaching a traffic signal as one of the candidates in which autonomous vehicles promise significant benefits. He simulates a signalized intersection with autonomous and human vehicles, assuming $t = 0.5s$ to be the time gap for autonomous, and $t = 1.5s$ the time gap for human-driven vehicles with altering demand and 5 different shares of autonomous vehicles (Wagner, 2016). It can be seen that the average delay time per vehicle mostly depends on the traffic demand at the intersection, but rises much slower for a high share of autonomous vehicles.

Our approach is based on these assumptions and provides a model of an existing intersection where these assumptions are tested using a microscopic simulation.

3. The considered Intersection in Munich, Germany

The considered intersection (on Lindwurm and Kapuziner Street in Munich) is on a main arterial road between the centre of Munich and the west of the city. The position of the intersection in Munich as well as the geometry of the intersection are shown in Figure 1. The intersection is flat and sufficiently visible, and a dry surface is assumed. The Lindwurm Street connecting East and West with traffic flows V1 and V3 is the main road with two lanes in each direction and separated bicycle lanes on each side. However, during the peak hours, the flows V2 and V4 on the collector street Kapuziner Street and Herzog Heinrich Street are quite high as well.

Average daily traffic volume is about 27,000 vehicles crossing the section Lindwurm Street, with a heavy traffic share between 1 and 8%. For the simulation, the peak hours in the morning (between 7:45 and 8:45 a.m.) and evening (between 4:30 and 5:30 p.m.) are considered, when up to 3,240 motor vehicles and 950 bicycles cross the intersection. As the intersection lies in the city centre with subway stations nearby, we assume the pedestrian movements to be around 300-400 persons per hour on each street of the intersection. The exact numbers of traffic volume considered in the calculations and simulations can be seen in Figure 2.

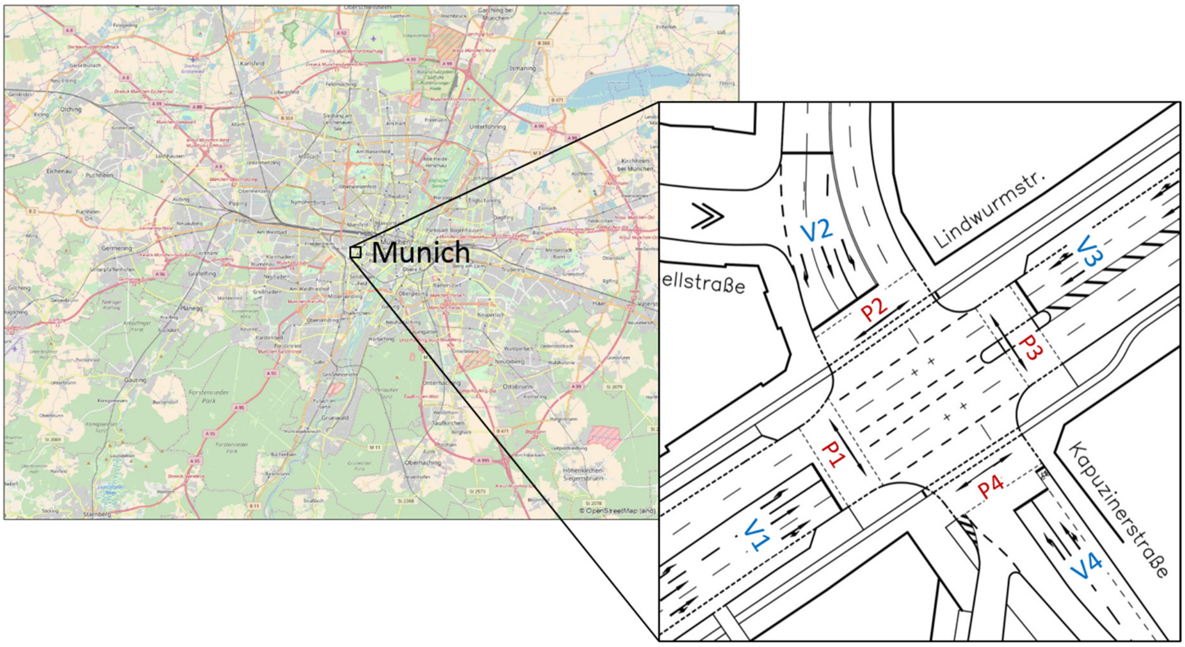

Fig.1 position of considered intersection in Munich, Germany, and geometry of the intersection

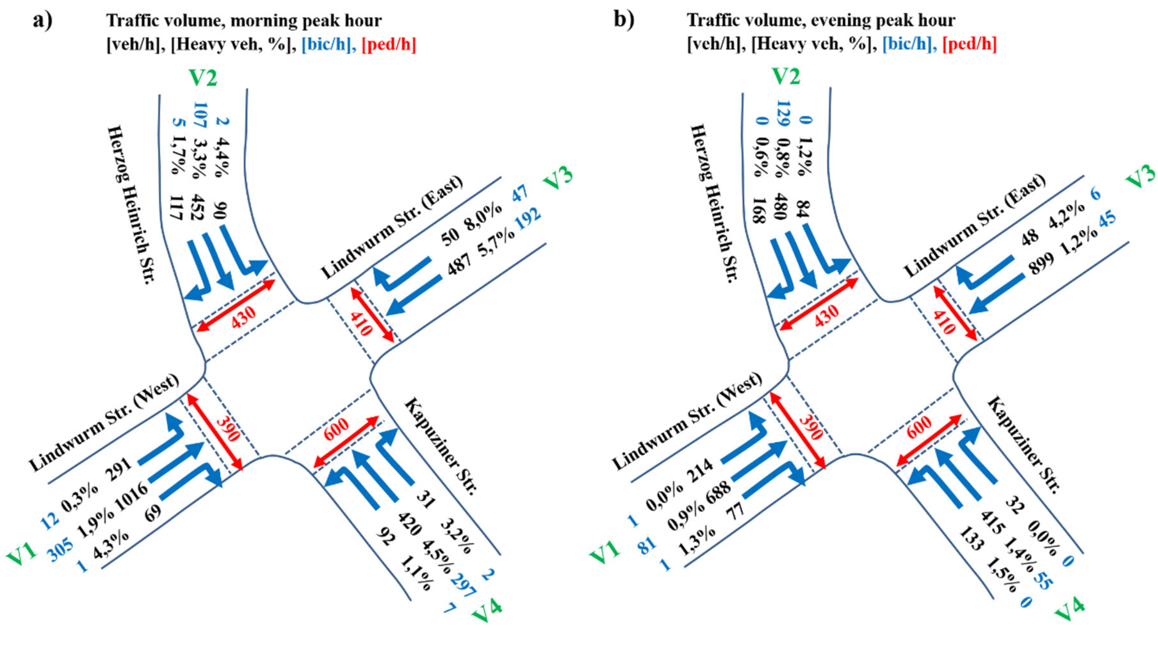

Fig. 2 traffic volume at considered intersection for a) morning peak hour and b) evening peak hour

The intersection is signalized with fixed signal programmes depending on the time of the day. The traffic signal programmes applied during the morning and evening peak hours have a cycle length of 90 seconds and are shown in Figure 3.

As our paper aims to assess the capacity impact of CAVs given the current situation of traffic demand and signal control, we apply the traffic demand and signal control as shown in the figures. This means, that we do neither apply a traffic actuated signal nor allow the CAVs to register at the intersection and influence the traffic light at the intersection. Due to the fact that pedestrians and bicyclists are an important part of the traffic demand at the considered intersection, the all red periods can also not be shortened. In the next chapter, we are going to present the results of the capacity calculation as well as the approach and the results of the microsimulation.

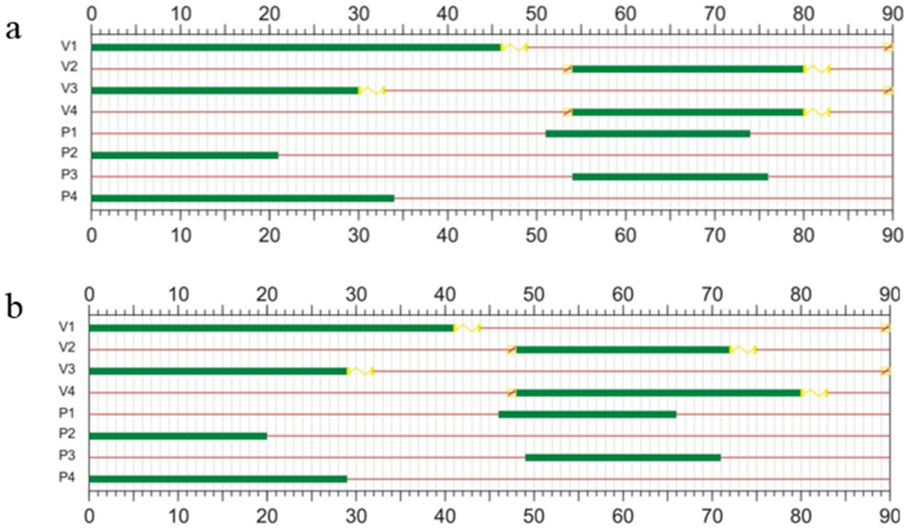

Fig. 3 Signal programme at considered intersection for a) morning peak hour and b) evening peak hour

4. Capacity Calculations and Simulations

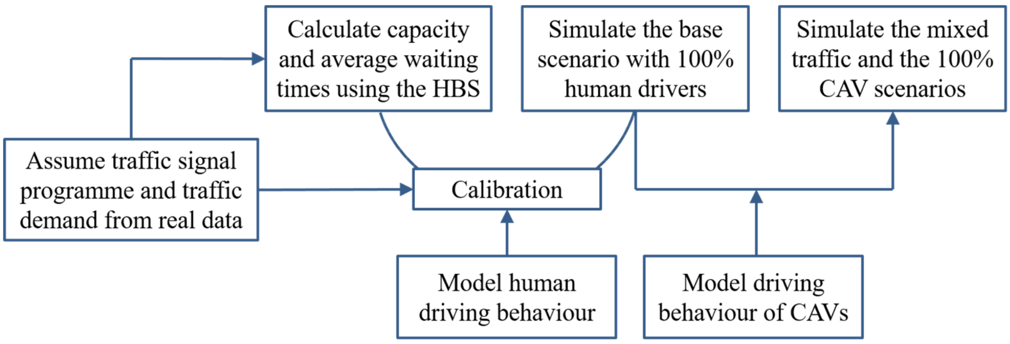

Fig. 4 Flowchart describing the capacity calculation and simulation approach

In this chapter, we explain the approach and the results of the capacity calculations as well as the simulation analyses. The approach is illustrated in Figure 4. First of all, we explain the assumptions made for the parameters of the simulation when modelling human driving behaviour and the driving behaviour of CAVs. Afterwards, we present the results of the capacity calculations and the simulation runs.

4.1 Parameters and Assumptions for the Simulation

In order to simulate traffic at a signalized intersection taking into account pedestrians, bicyclists, drivers in passenger cars and trucks as well as autonomous vehicles, parameters such as reaction times and acceleration behaviour are a crucial input. The most important considered parameters are presented in Table 1, and the underlying assumptions are explained in the following. At first point, it is important to understand the behaviour of human drivers. The main difference between human drivers and autonomous vehicles will be the inconsistency of human behaviour in comparison to the deterministic behaviour of autonomous vehicles. Let it be the acceleration at a traffic light, the gap to the leader vehicle or the reaction time in different situations, these parameters do not only differ between different human drivers but also between one single driver in several driving situations. In order to represent human driving behaviour as accurately as possible, we consider parameter values found in the literature. The intersection is simulated using the microsimulation software AIMSUN (version 8.2) by TSS. The micro simulator uses the Gipps following model (Gipps, 1981). Default values for input parameters are given in the paper by Anya et al. (2014). Most parameters used in our simulation are adjusted to the values recommended for the simulation of traffic on German freeways (Geistefeldt et al., 2017). These values are calibrated for German cars and drivers. However, due to the fact that we consider urban traffic instead of freeway traffic, we adapted some of the parameters and assumptions as explained below.

Table1. Setting of parameters in microscopic simulation

	Human Drivers	Autonomous Cars	Trucks	Bicycles
Reaction time [s]	Varying between 0.6 and 1.8 seconds mean: 1.1 seconds	0.6 seconds	Varying between 0.6 and 1.2 seconds mean: 0.8 seconds	0.6 seconds
Reaction time for front vehicle at traffic light [s]	Varying between 0.8 and 1.2 seconds mean: 1.0 seconds	0.6 seconds	Varying between 1 and 1.2 seconds mean: 1.1 seconds	0.8 seconds
Gap [sec]	Varying between 0.4 and 2 seconds mean: 0.8 seconds	0.6 seconds	Varying between 0.5 and 2 seconds mean: 1 sec.	Varying between 0 and 0.6 seconds mean: 0.2 seconds
Length [m]	Varying between 3.4 and 5.6 meters mean: 4.5 meters	Varying between 3.0 and 5.0 meters mean: 4.5 meters	Varying between 6 and 15 meters mean: 12 meters	1 meter
Distance between vehicles at full stop [m]	Varying between 0.5 and 2.6 meters mean: 1.5 meters	1 meter	Varying between 1 and 2.50 meters mean: 1.70 meters	Varying between 0.1 and 1 meters mean: 0.3 meters
Maximum acceleration [m/s²]	Varying between 2.6 and 4.5 m/s² mean: 3 m/s²	3 m/s²	Varying between 0.6 and 1.8 m/s² mean: 1.2 m/s²	Varying between 0.8 and 1.5 m/s² mean: 1.2 m/s²
Speed limit acceptance (SLA) [-]	Varying between 0.9 and 1.3 mean: 1.1	1.0	Varying between 1 and 1.1 mean: 1.05	1.0
Maximum desired speed (MDS) [km/h]	Varying between 100 and 200 km/h mean: 130 km/h	130 km/h	Varying between 70 and 85 km/h mean: 80 km/h	Varying between 15 and 30 km/h mean: 25 km/h
Preferred speed [km/h]	min(SLA × speed limit, MDS)	min(SLA × speed limit, MDS)	min(SLA × speed limit, MDS)	min(SLA × speed limit, MDS)

It was found out, that reaction times differ a lot depending on the person, and on the fact if that person is distracted or not (Hugemann, 2002). Additionally, reaction times can be differentiated into reaction times within regular traffic conditions and reaction times in accidents and other drastic and threatening situations (Hugemann, 2002). Reaction times in unexpected and dangerous situations are especially difficult to measure because they are hard to simulate. The mean reaction time obtained in a study by Zhang et al. (2016) is 1.2 seconds with a standard deviation of 0.4 seconds, which coincides with common legal recommendations considering the safety gap. We assume a slightly shorter reaction time, because we consider inner-city commuter traffic, when drivers are more experienced and attentive. Due to the reaction times, human drivers should respect a gap to the front vehicle of at least 0.9 seconds, and most official sources recommend a gap of around 2 seconds (Wagner, 2016). However, gaps are often shorter in urban traffic and especially during peak hours. We hence assume a mean gap of 0.8 seconds for human drivers, varying between 0.4 and 2 seconds.

The reaction time for the front vehicle at a red traffic light is even more dispersed than the general reaction time due to the fact that the reaction time is not crucial for the driver. Many different factors have an impact on the reaction time at a traffic light, e.g. the weather conditions and the duration of the red phase (Yanqun et al., 2013). The reaction times for following vehicles depend on their position in the queue (Yang et al., 2012). They observed a reaction time of around 2.2 seconds for the first vehicle and a decreasing reaction time for the following vehicles, as they already see the green light and are hence prepared to start driving. This results in a headway of around 1.8 seconds when crossing the traffic light. The value of 1.8 seconds is also used in the HBS (FGSV, 2015). In our simulation, we assume a reaction time of approximately 1 second for the first vehicle at the traffic light, because the traffic light has a red-yellow phase of 1 second already announcing the upcoming green phase. The maximum acceleration values for human driven cars and trucks were taken from an overview of acceleration behaviour studies (Lange, 2006). The values presented there coincide with the values presented by Rittger et al. (2015), where the acceleration and deceleration behaviour when approaching and leaving a traffic light was analysed.

The parameters and assumptions for bicycle behaviour (speed, acceleration and deceleration) are taken from the Dutch Manual for Planning Bicycle Infrastructure, which is summarized in Parkin et al. (2010). Obviously, acceleration and deceleration behaviour in the bicycle case highly depends on the slope of the considered intersection. In our case, the intersection shows no slope, which means we can use the average values for flat conditions. Pedestrians are simulated using the simulation extension Legion for Aimsun, see Alexandersson (2013) for an explanation. The parameters for pedestrian behaviour were not adjusted, as the focus of the simulation lies on evaluating the differences between human and autonomously driven vehicles instead of modelling pedestrian behaviour.

The main characteristic of CAVs is that the variations experienced with human drivers disappear. The acceleration and reaction times do not differ between several cars, but are identical. This means that CAVs can start almost simultaneously and cross an intersection in the same velocity. Traffic with a high share of CAVs is harmonized and shows smaller gaps between cars. We assume that CAVs respect a headway of 0.6 seconds (Friedrich, 2016). The mean acceleration value is not changed as compared to human drivers, because drivers need to feel comfortable when being driven by a CAV. Other than that, there is a lack in information about parameter values and hence a big need for research considering CAV driving behaviour and interaction (Calvert et al., 2017).

4.2 Results of the Capacity Calculation

First of all, the theoretical capacity and level of service (LOS) of the considered intersection is calculated according to the latest version of "Handbuch für die Bemessung von Straßenverkehrsanlagen (HBS) Stadtstraßen" – the German Manual for the Assessing of Road Traffic Facilities for Urban Roads (FGSV, 2015). The results for the morning peak hour are shown in Table 2, and the results for the evening peak hour in Table 3.

Table 2. Capacity of each direction [veh/h], morning peak hour

	Lindwurm Street West (V1)			Herzog-Heinrich-Street (V2)			Lindwurm Street East (V3)		Kapuziner Street (V4)	
Direction	V1 L	V1 S	V1 SR	V2 L	V2 S	V2 R	V3 S	V3 SR	V4 L	V4 SR
Capacity [veh/h]	443	1027	923	160	583	303	655	534	120	526
Occupancy rate [%]	65.6%	55.7%	55.6%	56.3%	77.6%	38.6%	45.2%	45.1%	76.7%	85.7%
Av. Waiting time [s]	35.4	17.2	19.9	44.5	45.0	35.9	25.6	29.6	53.6	66.5
Level of service [-]	C	A	A	C	C	C	B	B	D	D
Av. Queue length [m]	46.8	62.5	59.6	17.6	77.6	17.8	37.4	32.6	25.4	95.3

Table 3. Capacity of each direction [veh/h], evening peak hour

	Lindwurm Street West (V1)			Herzog-Heinrich-Street (V2)			Lindwurm Street East (V3)		Kapuziner Street (V4)	
Direction	V1 L	V1 S	V1 SR	V2 L	V2 S	V2 R	V3 S	V3 SR	V4 L	V4 SR
Capacity [veh/h]	263	926	760	141	551	243	637	568	152	677
Occupancy rate [%]	81.4%	45.4%	45.4%	59.6%	87.1%	69.0%	78.6%	78.5%	87.8%	66.1%
Av. Waiting time [s]	50.4	18.2	22.7	46.4	70.1	47.5	43.9	47.1	60.6	32.0
Level of service [-]	D	A	B	C	E	C	C	C	D	B
Av. Queue length [m]	49.6	45.6	41.4	17.6	104.5	32.8	85.4	78.3	43.2	64.7

The capacities of each street differ between the morning and evening peak hour due to the different traffic signal control plans that are applied. It can be seen that in the morning, Kapuziner and Herzog Heinrich Street (V4 and V2) show the highest occupancy and hence the highest average waiting times of up to 64 seconds and the lowest level of service. In the evening, the highest occupancy can be found in Herzog Heinrich Street and Lindwurm Street East (V2 and V3), with an average waiting time of up to 62 seconds.

4.3 Results of the Simulations

In a next step, the intersection is modelled and simulated in the Aimsun micro simulator and calibrated in order to fit the capacity calculations using the HBS. The results of the calibrated micro simulation as compared to the calculations are shown in Table 4.

Table 4. Comparison of waiting times between the HBS calculations and the microsimulation for the base scenario

	Lindwurm Street West (V1)	Herzog Heinrich Street (V2)	Lindwurm Street East (V3)	Kapuziner Street (V4)
Morning peak hour: avg. waiting time according to HBS-calculation [s]	22.1	43.3	27.4	64.3
Morning peak hour: avg. waiting time according to microsimulation [s]	21.4	45.1	23.8	65.7
Evening peak hour: avg. waiting time according to HBS-calculation [s]	26.8	62.2	45.4	38.5
Evening peak hour: avg. waiting time according to microsimulation [s]	26.0	59.9	41.3	36.3

This current state is the base scenario of our analysis. What effects will the different proportions of autonomous vehicles as a percentage of traffic have on the waiting times at each street of the intersection? To answer this question, additionally to the base scenario, ten different scenarios are implemented and tested, where an increasing share (10%, 20%, …, 100%) of vehicles is removed and replaced by CAVs. We simulate the traffic in the morning and evening peak for 120 minutes each. This time interval should be big enough to evaluate the performance of the intersection. For each scenario, 10 different replications are run and the average outcome is used. The results of the microsimulations are illustrated in Figure 5 and show that an increasing share of CAVs leads to shorter overall waiting times at the intersection as well as shorter waiting times in each street.

Considering the 100% replacement of passenger cars by CAVs, the overall waiting time at the intersection reduces from around 41 to around 27 seconds for the morning peak hour and from around 51 to around 28 seconds in the evening peak hour. It can be seen that the streets with the highest average waiting times in the base scenario show the highest potential for improvement. If we look at the Lindwurm Street (V1 and V3) for the morning peak hour, we can see that average waiting times in the base scenario are quite low with 21 seconds coming from the West and 24 seconds coming from the East. Considering that, arriving from the East, we have a green phase of 30 seconds out of 90 seconds cycle time, the average waiting time for a single vehicle arriving at an empty intersection at a random time is 20.3 seconds. This means that even under perfect traffic conditions the average waiting time cannot fall below this value. Therefore, the potential for a reduction in waiting time is limited. In general, let c be the cycle time of the traffic signal programme, and let r be the red time of the considered lane. Then the minimum average waiting time $t_{w_{min}}$ for a vehicle arriving at a random time is

$$t_{w_{min}} = \frac{r*(r+1)}{2*c} \tag{1}$$

The shown results match the observation of Wagner, who found out that CAVs have an impact on capacity, however, if the demand on a street is not at the capacity limit, the impact on waiting time is small (Wagner, 2016).

Looking at the scenarios with mixed traffic, it can be seen that the reduction in waiting time is not linear and does not show the same curve when comparing the different streets. In the morning peak hour, we observe an increasing average waiting time for mixed traffic with a little percentage of CAVs, and only for a share of at least 40% CAVs, the average waiting time falls below the average waiting time of the base scenario for all streets. In the evening, the reduction in average waiting time is already quite high in the 10% CAV case. We do not know why the results show this behaviour. As the rise in average waiting time does not occur on Lindwurm Stret (V1 and V3) but only on V2 and V4, we assume that it is due to the fact that vehicles going straight and turning vehicles share the same lane in the case of V2 and V4. However, this needs to be further investigated in the future.

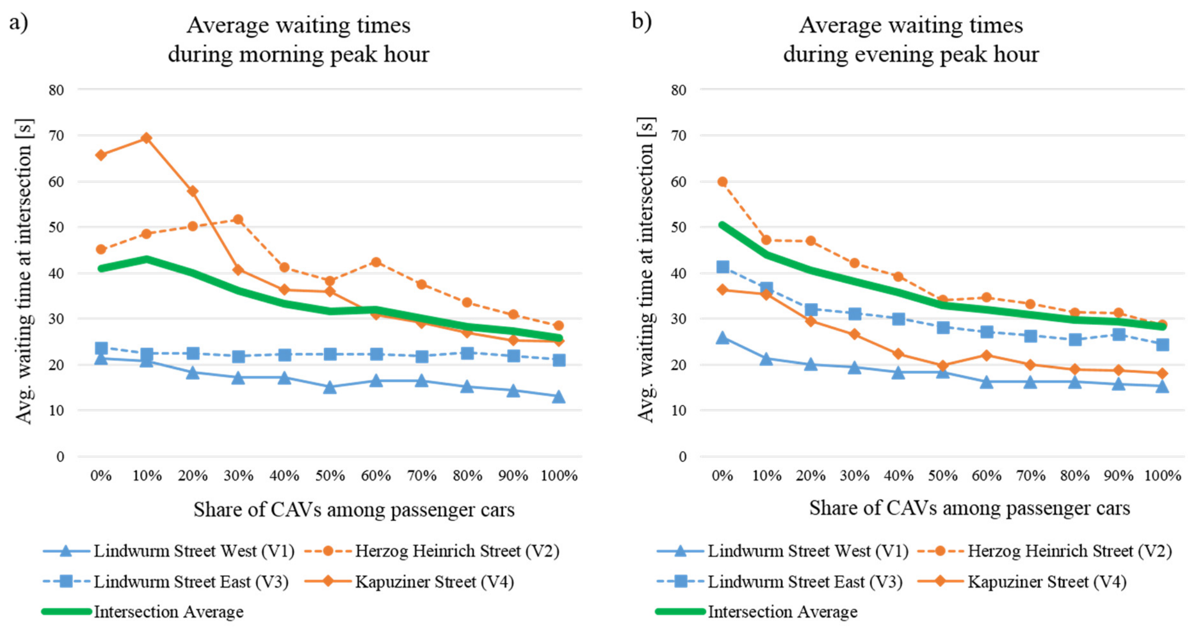

Fig. 5 Simulation results for a) morning peak hour and b) evening peak hour

5. Conclusion and Outlook

Our paper shows the current situation at a busy inner-city intersection during the peak hours in the morning and in the evening. We simulated the current traffic mix considering cars, heavy traffic, bicycles and pedestrians and compared it to several scenarios where humans share the road with CAVs. It can be seen that, under the assumed conditions, the average waiting times at the intersection can be reduced. Comparing the base scenario (0% CAVs) and the 100% replacement of passenger cars by CAVs, the overall waiting time is reduced by 34% in the morning peak hour and by 45% in the evening peak hour which is significant. This is due to the fact that the assumed reaction times for CAVs are smaller than the average reaction times of human drivers and that the driving behaviour of CAVs allows for a more harmonic traffic flow. The potential for improvement depends on the occupancy rate of the streets, the number of lanes, and the share of green time. If the occupancy rate of a certain street is low and waiting times are hence short, there is not much room for improvement, which can be observed in the case of Lindwurm Street East (V3) in the morning peak hour, for example. We assume that this result is valid for other intersections as well, but there is still some work to be done to validate the results.

When considering mixed traffic scenarios with a low penetration rate of CAVs, we could observe an increase in waiting time on V2 and V4 but not on V1 and V3. It has to be further investigated, if this is due to the fact that vehicles driving straight and turning vehicles share the same lane on V2 and V4. These findings have to be compared to analyses of other intersections to conclude generally valid effects. In future analyses, we also plan to examine not only one intersection but the effects considering green waves over a longer sequence of street sections, as well as traffic actuated signal control programmes. Additionally, the results depend on the assumptions made for the reaction times, acceleration and deceleration behaviour etc. As mentioned before, there is a lack in information about parameter values considering CAV driving behaviour and interaction (Calvert et al., 2017). A comparison of results depending on varying parameter values shall be conducted.

In general, the microsimulation is a suitable tool in order to assess the effects that CAVs will have on urban traffic system. Further studying these effects will be an important supplement to existing studies that investigate effects of CAVs on highways and freeways and do not take bicyclists and pedestrians into account.

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6. References

Alexandersson, S., Johansson, E., 2013. Pedestrians in microscopic traffic simulation. Master’s Thesis at the Chalmers University of Technology.

Anya, A., Rouphail, N., Frey, H., Schroeder, B., 2014. Application of AIMSUN Micro Simulation Model in Estimating Emissions on Signalized Arterial Corridors. Transportation Research Record: Journal of the Transportation Research Board, 2428, pp. 75-86.

Calvert, S., Wilmink, I., Farah, H., 2017. Next steps in describing possible effects of automated driving on traffic flow. Technical report, TrafficQuest Centre for Expertise on Traffic Management.

Chen, L. Englund, C., 2016. Cooperative Intersection Management - A Survey. IEEE Transactions on Intelligent Transportation Systems, Vol. 17, No. 2, pp. 570-586.

Di Fabio, U., Broy, M., Brüngger, J., Eichhorn, U., Grunwald, A., Heckmann, D., Hilgendorf, E., Kagermann, H., Losinger, A., Lutz-Bachmann, M., Lütge, C., Markl, A., Müller, K., Nehm, K., 2017. Automatisiertes und Vernetztes Fahren. Report of the Ethik-Kommission, Bundesministerium für Verkehr und digitale Infrastrukutr.

FGSV, 2015. Handbuch für die Bemessung von Straßenverkehrsanlagen. Forschungsgesellschaft für Straßen- und Verkehrswesen e.V., Köln.

Friedrich, B., 2016. The Effect of Autonomous Vehicles on Traffic. In *"Autonomous Driving"*, SpringerOpen, pp. 317–334.

Geistefeldt, J., Giuliani, S., Busch, F., Schendzielorz, T., Haug, A., Vortisch, P., Leyn, U., Trapp, R., 2017. HBS-konforme Simulation des Verkehrsablaufs auf Autobahnen. Berichte der Bundesanstalt für Straßenwesen, Unterreihe Verkehrstechnik, Heft 279.

Gipps, P., 1981. A behavioural car-following model for computer simulation. Transportation Research Part B: Methodological, Vol. 15, No. 2, pp. 105-111.

Hu, Y., 2016. Improving Coordinated Traffic Signal Timing through Connected Vehicle Technology. Doctoral Thesis at the Swanson School of Engineering, University of Pittsburgh.

Hugemann, W., 2002. Fahrerreaktionszeiten im Straßenverkehr. Proceedings of the EVU 2002 Slovenija, Portorož, September 06 - 07, 2002.

Krause, S., Motamedidehkordi, N., Hoffmann, S., Busch, F., Hartmann, M., Vortisch, P., 2017. Auswirkungen des teil- und hochautomatisierten Fahrens auf die Kapazität der Fernstraßeninfrastruktur. FAT-Schriftenreihe 296, Forschungsvereinigung Automobiltechnik e.V., Berlin.

Lange, F., 2006. Unfallrekonstruktion - Anfahrbeschleunigungen. Verkehrsrechtsreport, 10(2006), 377-382.

Levin, M., Boyles, S., 2016. A multiclass cell transmission model for shared human and autonomous vehicle roads. Transportation Research Part C: Emerging Technologies, Vol. 62, pp. 103-116.

Lioris, J., Pedarsani, R., Tascikaraoglu, F., Varaiya, P., 2017. Platoons of connected vehicles can double throughput in urban roads. Transportation Research Part C 77 (2017), pp. 292-305.

Parkin, J., Rotheram, J., 2010. Design speeds and acceleration characteristics of bicycle traffic for use in planning, design and appraisal. Transport Policy Vol. 17, Issue 5, 335-341.

Rittger, L., Schmidt, G., Maag, C., Kiesel, A., 2015. Driving behaviour at traffic light intersections. Cognition, Technology & Work, Volume 17, Issue 4, pp. 593-605.

Santa, C., Kaths, J., Mathias, P., Schendzielorz, T., 2014. Potenziale kooperativer Lichtsignalsteuerung zur Steigerung der Verkehrseffizienz und -sicherheit / Potential of cooperative signal control to increase traffic efficiency and safety. Straßenverkehrstechnik, Vol. 58, Issue 10, pp. 676-683.

TomTom International BEV, 2017. TomTom Traffic Index, https://www.tomtom.com/en_gb/trafficindex/, Accessed July 20, 2017.

United Nations, Department of Economics and Social Affairs, Population Division, 2014. World Urbanization Prospects: The 2014 Revision, Highlights.

Van Arem, B., van Driel, C., Visser, R., 2006. The Impact of Cooperative Adaptive Cruise Control on Traffic-Flow Characteristics. IEEE Transactions on Intelligent Transportation Systems, Vol. 7, No. 4, pp. 429-436.

Wagner, P., 2016. Traffic Control and Traffic Management in a Transportation System with Autonomous Vehicles. In *"Autonomous Driving"*, SpringerOpen, pp. 301–316.

Yang, S., Chung, E., 2012. Driver Response Time of Queuing Vehicles at Urban Intersections. Procedia – Social and Behavioral Sciences 43 (2012) pp. 169-177.

Yanqun, Y., Xinyi, Z., Sudan, J., Yifan, X., 2013. Drivers’ reaction time towards red-light timing at urban intersections. Procedia – Social and Behavioral Sciences 96 (2013), pp. 2506-2510.

Zhang, Y., Antonsson, E., Grote, K., 2006. A New Threat Assessment Measure for Collision Avoidance Systems. Proceedings of the IEEE ITSC 2006, Toronto, Canada, paper TB5.1.