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Simulation-Based Forecasting the Impacts of Autonomous Driving

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Abstract

Autonomous vehicles (AV) are currently one of the hottest topics in transportation. There are discussions among other things about safety (e.g. liability, insurance), impacts on urban planning (e.g. less parking) and new business models and current business models being at risk (e.g. AV taxi fleets replacing classical taxi services).
The purpose of this paper is not to discuss, if the autonomous cars are thread or opportunity, or if they will solve the current problems or bring more problems which is at the moment more philosophical than technical question, but to discuss which ways we can evaluate the impacts of autonomous vehicles on the traffic flow by different penetration rates. In other words, how we can evaluate the coexistence of autonomous and conventional vehicles in the transition phase or the world after the transition phase with microscopic simulation tools. Results suggest that in high speed environment (freeway) a huge increase of capacity can be achieved in dependency on headways and speed. In the urban area the performance of intersections will remains decisive.

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Keywords: microscopic simulation, autonomous vehicles, following model

1. Introduction

Autonomous vehicles (AV) have a huge potential to chance our mobility patterns in positive ways in the near future. Predictions summarized in [1] by the automotive industry expect self-driving cars to be available on the market within the next five years (e.g. Volkswagen 2019, GM 2020 or sooner, Ford 2020). The US Secretary of Transportation

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assumed that driverless cars will be in use in all parts of the world by 2025. UBER expects their shared vehicles fleet to be driverless by 2030.

Considering this foreseeable period until AVs will be on roads, first in mixed traffic and then eventually with a (close to) 100% market share, there is little knowledge about the impacts, also in standard simulation and modelling tools and practice. Thus, it is important to investigate opportunities and threats of AVs in different areas, e.g.:

- Road Safety: According to the WHO [2] drivers' errors account for a large portion of accidents. Considering the current experiences e.g. from Google with 700,000 miles and two recorded crashes it can be expected that AVs will reduce accident rates [3]. Ethical questions of AV crashes are discussed in [4].
- Security issues: Due to the higher automation AVs are more hackable than today's cars. Car [5]. The dimension of these security issues obviously increases with the share of AVs up to potential terroristic attacks via car hacking.
- Mobility sharing: The idea of mobility sharing is actually to a certain degree independent from the AV-topic. However, AV and mobility sharing can create together an increased efficiency and increased level of service, e.g. by using AV taxi fleets [7] [8], or different requirements for parking space [9] and thus potential changes in the urban land use [10].
- Mobility patterns: AV trips might be considered more attractive than classical driving, as the time can be used for other things. Furthermore, costs might be different in particular with shared mobility. This will have impact on destination, route and mode choice [10]
- Capacity/Effectiveness: It is also often expected that AVs will lead to increased capacities due to higher effectiveness.

In this paper we focus on the last area of increased capacity & effectiveness due of AVs compared to classical cars. Friedrich [11] presented a study on this topic based on macroscopic considerations identifying particularly decreased gaps and possible higher speeds at equal density as reasons for higher capacity with AVs. Ambühl et al [9] developed the fundamental diagram based on mesoscopic simulations. In contrast to these macro- and mesoscopic analyses we present a microscopic simulation framework to analyze microscopic effects and apply this framework to selected situations on urban roads and freeways.

The remainder of the paper is structured as follows:

- Chapter 2: "Simulation framework": describes the possibilities and approaches for simulating autonomous vehicles together with conventional vehicles.
- Chapter 3: "Simulation study": informs about performed simulation tests and evaluations.
- Chapter 4: "Conclusions": summarizes the findings and recommendations.

2. Simulation framework

For analyzing the impact of autonomous vehicles, we use a microscopic traffic flow simulation. Within the simulation single vehicles behaviors are calculated according to the algorithms of the simulator. One core element of today's microscopic simulation models is the modelling of human behavior. In order to simulate autonomous vehicles, these algorithms need to be adjusted to simulate their behavior. If such an algorithm of autonomous vehicles behavior is implemented in the simulation, it is possible to evaluate the impacts of the autonomous vehicles. However, it is yet not clear how autonomous vehicles will behave in traffic. There is different assumption, such as autonomous vehicles should behave like humans, because other conventional drivers (in case of mixed traffic between autonomous vehicles and conventional drivers) may not be able to cope with the different autonomous vehicle behavior [6]. Other approaches optimize the emissions of vehicles [12] whereas other algorithms optimize traffic flow [13, 14]. Still there are different possibilities how an emission optimized autonomous vehicles behavior or a traffic flow optimized autonomous vehicles could be described. This paper does not intent to present an optimized autonomous vehicles behavior model. We describe how different autonomous vehicle behaviors will affect the traffic in our existing road networks. Therefore, we will make some assumptions on the behavior of autonomous vehicles.

The requirements of the microscopic traffic flow simulation tool to analyze the impact of autonomous vehicles are the following: The simulator need to be able to simulate interaction of vehicles. Thereby, the vehicles may have different driving behaviors (e.g. conventional and autonomous vehicles behavior). The interaction of vehicles includes car following and conflict handling (e.g. signal control, yield control, merging, lane changing, etc.).

The microscopic traffic flow simulation we use is PTV Vissim ([15], [16]). PTV Vissim is widely used to simulate traffic operations in urban, rural and freeway environment. The simulation uses the car following behavior of Wiedemann [17]. One approach to model autonomous vehicles is to change the driving behavior parameters of the Wiedemann model. The Wiedemann model is a psycho-physical car following model which models human behavior with the assumption that drivers can’t keep a specific distance to the leading car. This will make the vehicle oscillating around the desired distance to the leading vehicle. Also, the assumption in the model is that the driver can’t keep his desired speed exactly and therefor he oscillates around his desired free flow speed. In PTV Vissim the parameters of the Wiedemann model can be adjusted in a way to deactivate the oscillation.

In addition to the Wiedemann model it is possible to implement other algorithms for vehicle behavior, such as another autonomous vehicle driving behavior. There are three APIs in PTV Vissim to implement an external driving behavior, COM Interface, “DriverModel” – Interface and “DrivingSimulator”-Interface.

COM Interface is a Microsoft interface in order to externally control applications on Microsoft operation system [18]. Using the COM interface, you can access all attributes of the simulator plus there are specific functions of vehicle operations during the simulation. For example, it is possible to change the position and speed of a vehicle during the simulation. Using this functionality, you can model your own autonomous vehicles behavior using this interface. The DriverModel API is an interface designed to implement an external driving behavior. The simulator passes the information about the surrounding of a vehicle to the interface. This information contains the position, speed and acceleration of the surrounding vehicles, the upcoming signal state, the state of a priority rule, etc. In addition, the simulator sends a proposed action about how the simulator would simulate the vehicle to the interface. Using this API you can return to the simulation the acceleration, lane change information, etc. back to the vehicle [19]. While the DriverModel API provides only the relevant information about the surrounding of a single vehicle over the interface, the DrivingSimulator API provides the information of all vehicles in the network plus other information, for example all signal states as one package to the interface [20]. For externally simulated vehicles by the DrivingSimulator API the position, orientation and speed needs to be returned to PTV Vissim. Using the interface, one does not necessarily need to make use of a real driving simulator, instead you can also plug in your autonomous vehicles algorithm using this interface. The possibilities using the APIs to model a specific autonomous vehicles behavior was not used in this paper. Using the COM Interface or the DrivingSimulator API it is possible to connect a high accurate vehicle dynamics simulation to the microscopic simulator in order to perform a co-simulation of the traffic simulation plus a detailed vehicle simulation including the powertrain [21].

Table 1. Description of different APIs in PTV Vissim to simulate different aspects autonomous vehicles

	COM Interface	**DriverModel**	**DrivingSimulator**
Use Case	Ext. control of behavior, Veh. communication, Platooning	Appling external driving behavior	Human in the loop Soft-/Hardware in the loop
Programming language	All (Python, VBA, Java, Matlab, C#, C++…)	C++	C++
Responsible for car-following	Either PTV Vissim or API	Either PTV Vissim or API	API
Responsible for lane change	PTV Vissim	Either PTV Vissim or API	API
Responsible for routing	PTV Vissim	PTV Vissim	API

3. Simulation study

This chapter will briefly describe the setup and results of performed simulations. A python script was used to perform high number of simulations with variation in selected parameters of driving behaviors. For each combination of parameters at least 20 simulation runs where performed with different random seed number (stochastic variations in input). Averages are calculated and shown in figures and diagrams. In the result several thousand simulations were performed for each scenario.

Vissim model includes an improved version of Wiedemann's 1974 car following model (W74) with three adjustable parameters:

- Standstill distance (ax): Defines the average desired distance between two cars. The tolerance lies between -1.0 m and +1.0 m which is normally distributed at around 0.0 m, with a standard deviation of 0.3 m.
- Additive part of safety distance (bx_{add}): Value used for the computation of the desired safety distance d. Allows to adjust the time requirement values.
- Multiplicative part of safety distance (bx_{mult}): Value used for the computation of the desired safety distance d. Allows to adjust the time requirement values. Greater value = greater distribution (standard deviation) of safety distance.

The desired distance d is calculated from: d = ax +bx where:

- ax: standstill distance
- $bx = (bx_{add} + bx_{mult} * z) * \sqrt{v}$ where v: vehicle speed [m/s] z: is a value of range [0.1], which is normally distributed around 0.5 with a standard deviation of 0.15

PTV Vissim also offers another model based on Wiedemann's 1999 car following model (W99), where the following process is adjustable through nine driving behavior parameters (CC0...CC9):

- Standstill Distance (CC0): the average desired standstill distance between two vehicles. It has no variation. Headway Time (CC1): It is the distance in seconds which a driver wants to maintain at a certain speed. The higher the value, the more cautious the driver is. Thus, at a given speed v [m/s], the average safety distance is computed as: $dx_{safe} = CC0 + CC1 \cdot v$
- The safety distance is defined in the car following model as the minimum distance a driver will maintain while following another vehicle. In case of high volumes this distance becomes the value, which has a determining influence on capacity.
- Following variation (CC2): It restricts the distance difference (longitudinal oscillation) or how much more distance than the desired safety distance (dx_{safe}) a driver allows before he intentionally moves closer to the car in front. If this value is set to e.g. 4 m, the following behavior results in distances between dx_{safe} to dx_{safe} + 4 m. Smaller values for CC2 lead to more stable following behavior.

For description of other parameters which were not varied in this study and used with the default values see the literature ([12], [16], [17]). Selected driving parameters for following process, which influence the headways between vehicles (and through this the lane capacity), have only 50 % of the default value used for conventional vehicles:

Table 2. Default values for conventional and assumed values for autonomous vehicles

	Conventional vehicles	**Autonomous vehicles (assumption)**
Standstill distance	ax (W74) = 2, CC0 (W99) = 1.50 m	ax (W74) = 1, CC0 (W99) = 0.75 m
Additive part of safety distance (W74)	2.0 [-]	1.0 [-]
Multiplicative part of safety distance	3 [-]	1.5 [-]
Headway time CC1 (W99)	0.9 s	0.45 s
Following variation CC2 (W99)	4 m	0 m

In addition, the HGV share and the AV share in the traffic flow were varied in simulations from 0 to 100 %.

3.1. Capacity of urban roads (W74 model used)

Impact of following headway

In this case, the influence of following headway on the link capacity was tested. Following headway was varied by ax and bxadd parameters.

- Conditions: Cars only, 50 km/h desired speed, default driving behavior values (except variables)
- Variables: W74ax (average standstill distance, from 0.50 to 2.00 with 0.05 steps), W74bxadd (additive part of safety distance, from 0.50 to 2.00 with 0.05 steps)

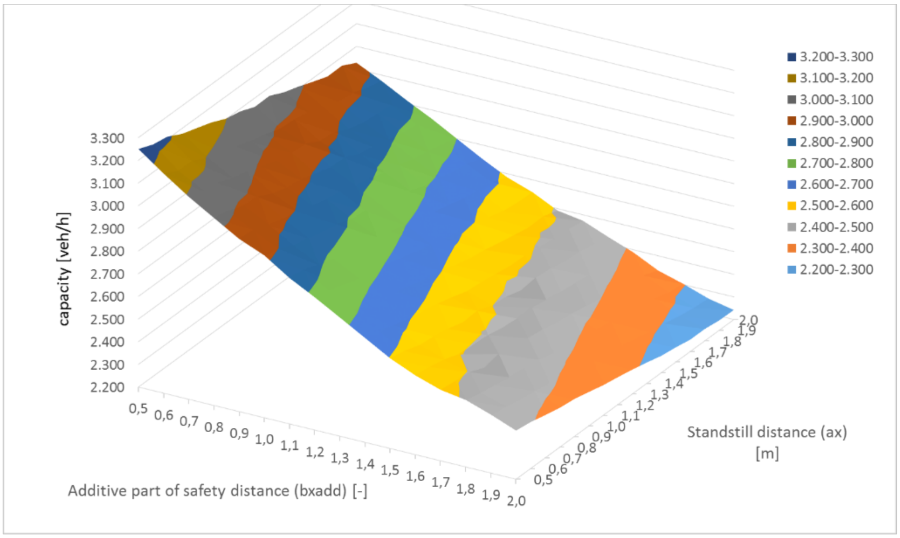


Figure 1. One lane link capacity in dependency on ax (average standstill distance) and bx_{add} (additive part of safety distance)

If we compare the values showed in Figure 1, we see that with the default parameters values the capacity is 2,240 veh/h (the lowest value in Figure 1). With the reduction of ax or bx_{add} the capacity increases. With 50 % reduction of ax and bx_{add} values, the capacity increases to 2,820 veh/h, which is 25.9 % more than with default values. Extreme reduction of these two parameters (to 0.50) leads to capacity of 3,250 veh/h, which is 45.1 % higher than the default capacity. It is easy to recognize that the additive part of safety distance has much higher influence on the capacity than standstill distance. Increase of the link capacity based on smaller following headway seems to be linear in low speed environment, but in the urban area the capacity of the intersection will be decisive for overall traffic performance.

Impact of penetration rate of autonomous vehicles (Figure 2a**)**

In this case, the influence of the penetration rate of the autonomous vehicles in the traffic flow was tested. Compared to previous test, the multiplicative part of safety distance for AV´s was set to 50 % of the default value (smaller value = smaller standard deviation of safety distance).

- Conditions: Cars only (conventional + autonomous), 50 km/h desired speed (linear distribution 48 – 52 km/h).
- Variables: AVs penetration rate (0..100 %)

If we increase the penetration rate of AV´s, the capacity increases too. Figure 2a shows almost linear increase of the base capacity (however exponential trend line fits the results slightly better). Full penetration brings additional 48.2 % of link capacity.

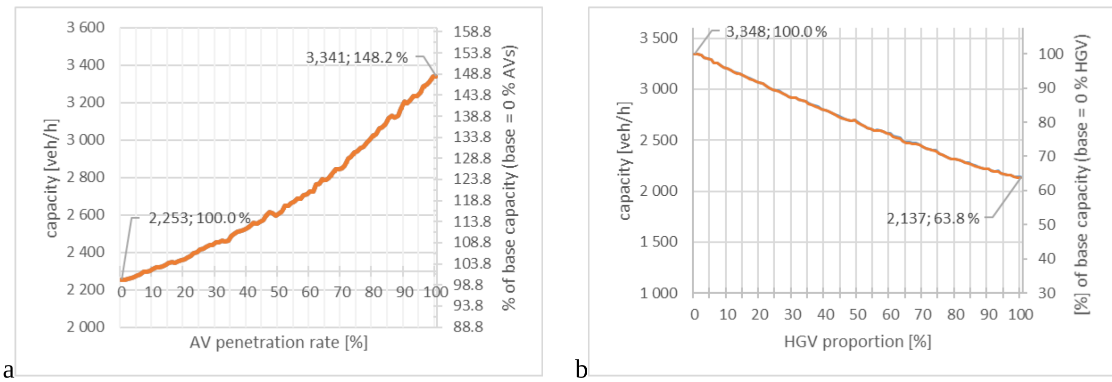


Figure 2. (a) One lane link capacity in dependency on AV penetration rate; (b) One lane link capacity in dependency on HGV share

Impact of autonomous HGV proportion in the AV traffic flow (Figure 2b)

In this case the influence of the HGV proportion in the traffic flow on the link capacity was tested.

- Conditions: AVs only, 50 km/h desired speed (linear distribution between 48 and 52 km/h).
- Variables: HGV proportion in the traffic flow (0..100 %)

If we assume, that all vehicles are autonomous including HGV´s, the HGV rate will influence the one lane link capacity almost linearly. 100 % HGV share means capacity drop to 63.8 % of the capacity with cars only in low speed environment. It corresponds to a HGV factor of 1.57. This case as all others is simplified to traffic on one lane link without any other interactions like signals or parking maneuvers, which can have more significant influence on the overall traffic performance. Therefore, the resulting trend is more interesting than the absolute capacity values.

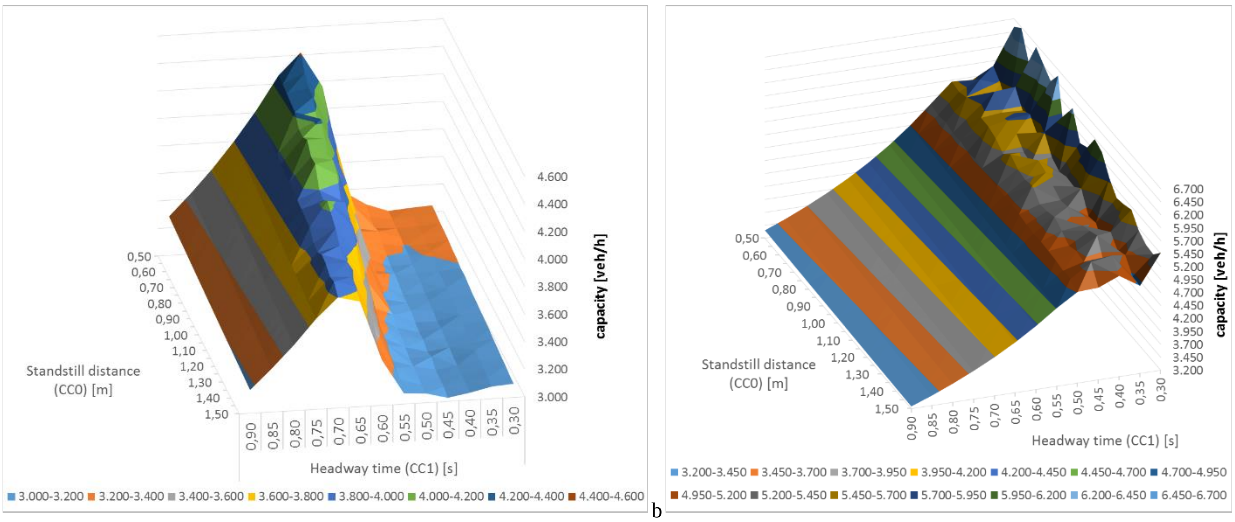
3.2. Capacity of freeway (W99 model used)

Impact of following headway

In this case the influence of following headway on the link capacity was tested. The following headway was varied by two parameters: CC0 and CC1.

- Conditions: desired speed 100 km/h (linear distribution between 95 und 105), cars only
- Variables: CC0 (average desired standstill distance, from 0.30 m to 0.90 m with 0.05 steps), CC1 (headway time, from 0.50 s to 1.50 s with 0.05 steps), CC2 =4 (Figure 3a) and CC2 = 0 (Figure 3b)

In high speed environment a huge increase of the capacity can be achieved by changing following headway. Decreasing the headway time shows a steep increase of the capacity to the peak around the headway time of 0.60 followed by decrease back to the base values and even below (see Figure 3a). This is caused by slightly different desired speeds of the vehicles in combination with other driving behavior parameters, especially CC2 – it restricts the distance difference (longitudinal oscillation) or how much more distance than the desired safety distance a driver allows before he intentionally moves closer to the car in front. As a result, disturbances arise in the traffic flow and the speed drops – that leads to capacity drop (see Figure 3a).



a b

Figure 3. (a) One lane link capacity in dependency on CC0 (average desired standstill distance) and CC1 (headway Time) with CC2 = 4 m; (b) One lane link capacity in dependency on CC0 (average desired standstill distance) and CC1 (headway Time) with CC2 = 0 m

Although the increase of the capacity to around 4,000 veh/h would be very big change for the traffic network, theoretically there is a potential to increase the capacity even more than Figure 3a shows for headways smaller than 0.60 s – but it this case also other parameters need to be changed. If we assume that autonomous vehicles will have very stable following behavior (oscillation in following reduced in PTV Vissim by setting “following variation” parameter CC2 to zero) and the headway time & standstill distance will be stepwise decreased, then based on simulation results (see Figure 3b), a strong increase up to 106 % (from 3,244 to 6,686 veh/h) could be achieved with desired speed around 100 km/h. As you can see on the chart (see Figure 3b) headway times bellow 0.5 s lead to disturbances in the traffic flow and the capacity stagnates. It seems that the results are touching the theoretical ceiling for Wiedeman99 following model (without any communication or cooperation between vehicles) at used desired speed. Real tests with automated vehicles (e.g. CoExist project) showed, that also smaller headways are possible, but with appropriate communication and cooperation of vehicles, where the vehicles can act (e.g. accelerate or decelerate) simultaneously. Figure 3 also shows that CC1 parameter (headway time) has the major impact on the capacity.

Impact of penetration rate of autonomous vehicles

In this case, the impact of AV penetration rate in the traffic flow was investigated for 3 different desired speeds.

- Conditions: desired speed 50 (48-52), 100 (99-101) and 130 km/h (125-135) – all speeds linearly distributed between min and max values, cars only in the traffic flow
- Variables: AV´s penetration rate (0...100 %)

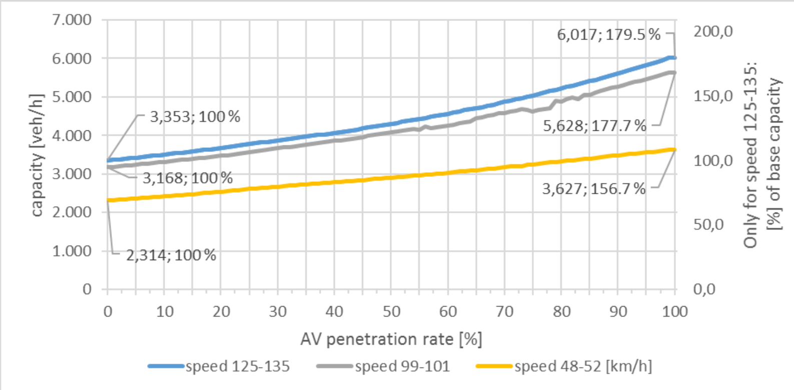


Figure 4. One lane link capacity in dependency on AV´s penetration rate

Figure 4 shows logical expectation, that with higher speed higher capacity increase can be achieved. The increase of the capacity is almost linear with the AV penetration rate at lower speed, but with slightly higher gains with larger penetration rates (> 60 %), especially at higher speeds.

Impact of HGV proportion in the traffic flow

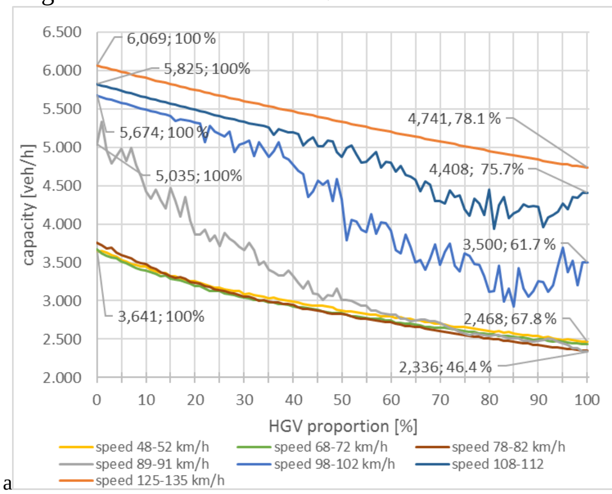
In this case, the impact of HGV proportion in the traffic flow was tested.

- Conditions: desired speed 130 (125-135), 120 (118-122), 110 (108-112), 100 (98-102), 90 (88-92) and 50 (48-52) km/h, AV´s only
- Variables: HGV penetration rate (0...100 %)

Figure 5 shows that the character of the change in capacity with different share of HGV´s is dependent on the speed. We can recognize three logical parts in the figure. The first one with desired speeds 50, 70 and 80 km/h: here the resulting capacity is relatively low and very similar, because the flow is full of disturbances (shock waves) from the begin of the simulation. The second part incorporate the desired speeds 90, 100 and 110 km/h. The flow is still unstable, but we can see that the higher the desired speed, the longer can the flow stay stable. The third part is represented by the desired speed 130 km/h – we can see that the flow is stable, it goes slowly down with increasing HGV`s share (almost linearly), but the disturbances in the traffic flow does not occur anymore. 100 % HGV´s share drops the capacity to 78.1 % (from 6,069 to 4,741) by desired speed 130 km/h. This corresponds to the HGV factor 1.28 for HGV`s with the length of 10,2 m. The HGV factor for lower desired speeds (50, 70, 80) would be around 1,53, for the other desired speeds in-between (90, 100, 110), the shape is not linear and thus a definition of one factor would be not satisfying.

Higher speed = higher spatial headways = higher flow stability?

The simulations are based on constant temporal headway (0.45 s), so the spatial headway is speed-dependent. Another test aimed on the flow stability shows how the maximum flow changes during the simulation (see Figure 5b) without the influence of HGV`s. Again, the flow is very unstable and thus relatively low at relative speeds 50, 60, 70, 90 km/h from the simulation begin (around 60 veh/min). At desired speed 100 and 110 km/h the maximum flow (measured in one-minute intervals) drops in couple of minutes even under the values of lower desired speeds. At desired speed 120 km/h the flow drops down also, but much later and much slower. Figure 5 shows average results from 20 simulation runs for each desired speed. With the desired speed 130 km/h the special headways are big enough to result into stable flow with the Wiedemann99 following model. In the Wiedemann99 following model, the closer vehicles are to their standstill distance the higher is their deceleration. With higher speeds, the ratio of the standstill distance to the spatial headway is larger with leads to less deceleration and more stable flow, especially for smaller headway times. Please note, that the desired speed mentioned in the paper and also in Figure 5 is not the real (achieved) speed, but the desired speed = the speed the vehicles "want" to drive. The real speed is a result of driving parameter settings and vehicle interactions.



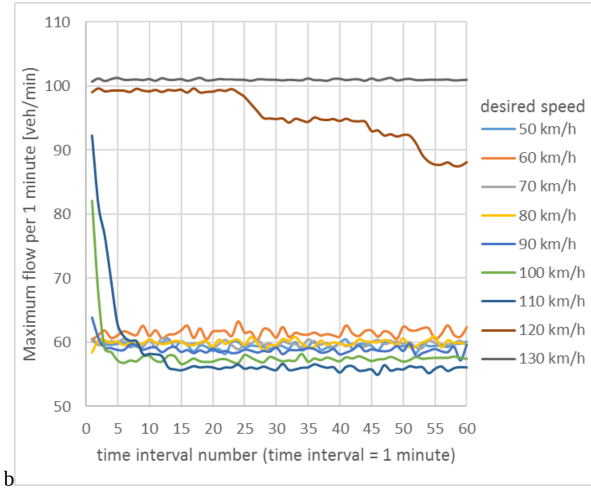


Figure 5. (a) One lane link capacity in dependency on HGV share and desired speed; (b) Flow stability with different desired speeds (cars only), Wiedemann99 following model (CC0 = 0,75 m, CC1 = 0,45 s, CC2 = 0 m)

4. Conclusions

There are several ways to simulate autonomous cars and thus investigate their impacts on the capacity of the road network. The exact way is based on integrating AV control logic via API into a simuation - this is suitable for users who have access to the AV control logic (including perception issues & vehicle dynamics) in detail and can connect an external AV simulator with the microsimulation software. This is usually only available for AV manufacturers and related researchers. The other group of users who do not own or do not know an AV control logic in detail (e.g. traffic planers & consultants) can perform simulations based on simplified assumptions about the autonomous car behavior, like assumption that the autonomous car will drive with a following headway which equals to 50% of an average headway for conventional cars with human drivers. For some such assumption it is possible to choose the easier way of changing driving behavior parameters instead of an API approach.

All simulation studies in this paper are simplified to traffic on one lane streets without any other interactions like signals or parking maneuvers, which can have more significant influence on the overall traffic performance. Also, no communication or cooperation features & strategies are incorporated. All results need to be seen as hypothetical, based on selected assumptions.

In urban area the increase of the link capacity based on smaller following headway and Wiedemann74 following model is moderate in low speed environment, so in the urban area the capacity of the intersection will be decisive for overall traffic performance. Theoretically, 50 % reduction of standstill distance and additive part of the safety distance leads to the capacity increase to 2,820 veh/h, which is 25.9 % more than with default driving behavior parameters. Extreme reduction of these two parameters (to 0.50) leads to capacity of 3,250 veh/h, which is 45.1 % higher than the default capacity (see Figure 1). Of course, the additive part of safety distance has much higher influence on the capacity than standstill distance. If we reduce also the multiplicative part of the safety distance, even higher capacity can be achieved. Assumption of 50 % reduction of all free Wiedemann74 following behavior parameters leads to the capacity of 3,341 veh/h. Impact of the AV-penetration rate is almost linear (see Figure 2).

If we assume, that all vehicles including HGV´s are autonomous, the HGV rate will influence the one lane link capacity almost linearly. 100 % HGV share means capacity drop to 63.8 % of the capacity with cars only in low speed environment (see Figure 2b). It corresponds to HGV factor of 1.57 (HGV´s with the length of 10.2 m simulated).

In the freeway area or in high speed environment a huge increase of the capacity can be achieved by changing following headway. If we assume that autonomous vehicles will need only 50 % headway in comparison to conventional vehicles with human drivers and the oscillation in the following process will be minimized, then based on simulation results the capacity could theoretically reach 6,000 veh/h at desired speed about 130 km/h. The desired speed plays a crucial role – only high speed above 120 km/h leads to stable flow if the input volume is maximized (higher than the capacity). Lower speeds lead to disturbances in the flow (see Figure 5) and this raises the question if the higher speed leading to higher spatial headways (if the temporal headway is fixed) will lead to more stable flow.

Although PTV Vissim allows to change several driving behavior parameters and reduce explicit stochastics (if this is in line with assumptions about the driving behavior of automated vehicles), there are still some implicit stochastic terms, which are not accessible by the user yet. This will be possible to overcome in future PTV Vissim versions.

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