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Simulating the impact of privately owned automated vehicles within the region Test Bed Lower Saxony, Germany

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Abstract

Automated and connected vehicles are assumed to have a major impact on road safety, traffic flow, energy consumption, greenhouse gas emissions, as well as on future mobility. This paper aims to analyze, the impact of privately owned automated vehicles on travel behavior in the region covering the Test Bed Lower Saxony in Germany. The main focus is laid on the evaluation of long-distance trips in the entire study area as well as on commuter journeys to and from the city of Brunswick. An agent-based demand model in conjunction with a traffic flow model was used to simulate four scenarios with different penetration rates of fully automated vehicles. The results show a major shift in the mode share, an increasing of the daily mileage, and reduced travel time of the motorized individual transport, as well as minor changes in travel distance and total traffic volume.

Keywords: agent-based simulation; automated vehicles

1. Introduction

Automated and connected vehicles are expected to have a significant impact on the future transport system. Currently, most traffic accidents within Germany are due to incorrect human behavior rather than technical errors [1]. Therefore, fully automated vehicles have the potential to reduce the number of accidents and increase road safety. Furthermore, these vehicles are expected to drive more efficiently and improve traffic flow, which could contribute to lower energy consumption [2] and savings in greenhouse gas emissions [3]. In addition, time on board could be used for activities that are not related to driving. In particular, commuters could get some of their office work done or relax while riding. These self-driving cars can also become attractive for new user groups, like disabled people, elderly, as

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well as people without driver‘s license. But, the studies above also mentioned, that an increasing travel demand could also lead to a higher traffic volume, which may negate the potential energy and emission saving effects.

Technical aspects, such as the future road infrastructure, driving style, as well as the communication between vehicles and the infrastructure can be tested with the help of test fields for automated and connected vehicles. Furthermore, these test areas can be used to explore new mobility concepts in both motorized individual transport and public transport. Whereas, the consequences of the future usage of automated vehicles are often evaluated through simulations. Here, a reduction or replacement of the privately owned vehicle fleet and the introduction of new mobility services are assumed in many cases [4][5][6]. Recent research shows, that privately owned vehicles have gained a new comfort factor as a result of the COVID-19 pandemic [7]. Due to the potential long-term effects on future mobility behavior and the fact that the vehicle fleet in Germany is still growing, this contribution assumes that conventional cars will be replaced by privately owned self-driving cars instead of downsizing the vehicle fleet.

This paper aims to analyze, the impact of fully automated vehicles on travel behavior in the region covering the Test Bed Lower Saxony in Germany [8]. It is assumed, that the potential of self-driving cars is more likely to be seen on long journeys as well as for commuters. Therefore, the main focus is laid on the evaluation of long-distance trips in the entire study area as well as on commuter journeys to and from the city of Brunswick. For this purpose, four scenarios with different penetration rates of fully automated vehicles were simulated.

The paper is structured as follows: Section 2 gives information on the simulation framework. The scenarios are outlined in Section 3, whereas the results of the simulations are given in Section 4. Finally, Section 5 includes the conclusions.

2. Simulation Framework

In this section, the simulation framework will be outlined. First, an overview of the study area is given, followed by a introduction of the applied transport models. Finally, the approaches used for simulating the impact of automated vehicles are explained.

2.1. Study area

With the Test Bed Lower Saxony, a research infrastructure for automated and connected vehicles is currently being created. The test field includes sections of various highways, but also parts of federal and country roads. Furthermore, it also integrates the roads of the Application Platform for Intelligent Mobility (AIM) [9], which is in operation within the city center of Brunswick. In total, the test field will cover more than 280 road kilometers after completion. This road network is located in the federal state of Lower Saxony within the districts of Gifhorn, Helmstedt, Hildesheim, Peine, Hanover region, as well as Wolfenbüttel and the district-free cities of Brunswick, Salzgitter, and Wolfsburg. The area has been subdivided into 2807 Traffic Analysis Zones (TAZ). Therefore, a suitable sub-division by neighborhoods containing approximately 500 households per TAZ was obtained from Nexiga [10]. The region is mainly characterized as urban. Figure 1 shows the spatial coverage of the study area including the road network of the Test Bed Lower Saxony and the division into traffic zones. The geographical position within Germany is given in the overview image at the lower left corner, highlighted in dark gray.

2.2. Applied transport models

The agent-based transport model TAPAS [11][12] is used to estimate the travel demand in the presented study area. Within a simulation run, TAPAS calculates the activities and trips performed during a day for each person in the related synthetic population. Thereby, it provides individual trip chains with specific spatial and temporal information, as well as a detailed description of each person and the associated household as simulation output. The sum of these trips results in an overall picture of the travel demand within the study area. Finally, the travel demand obtained from TAPAS is assigned to the road network using the traffic flow model SUMO [13]. The linkage of these two models is realized by feedback of travel times [14]. Both transport models are available as open source and can be found at: https://github.com/DLR-VF/TAPAS respectively https://github.com/eclipse/sumo.

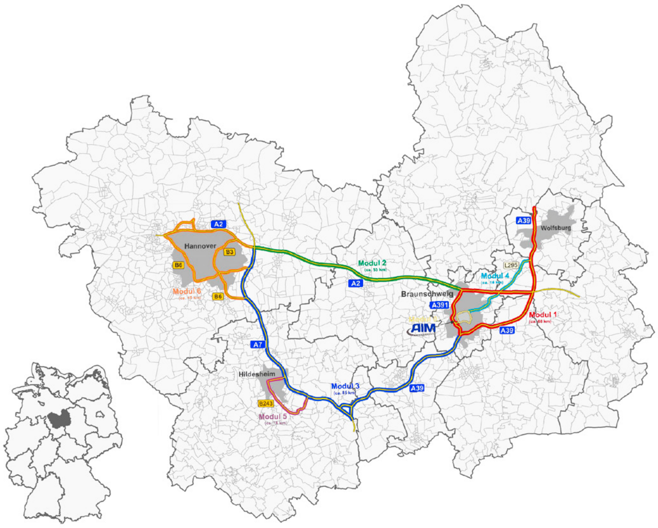

Fig. 1: Spatial coverage of the study area including the road network of the Test Bed Lower Saxony and the division into traffic zones. The geographic location within Germany is highlighted in the overview image.

2.3. Approaches used for simulating the impact of automated vehicles

In order to reflect the impact of automated vehicles in travel demand models, the mode choice has to be adjusted accordingly [15]. Three important aspects are mentioned in this context. First, it is necessary to subdivide the motorized individual transport mode more precisely, e.g., to distinguish between a conventional and an automated vehicle. In addition, the inclusion of new user groups should be considered. But above all, the travel time should be split into separate parts, as it is the most important factor in the mode choice. The simulated vehicle fleet in TAPAS is therefore divided into different car types in terms of powertrain, car size, and automation level according to SAE levels [16]. TAPAS distinguishes between the various car types as described in [11]. The penetration rate of each vehicle segment can be modified. Automated driving on SAE level 5 does not require an active driver possessing a driving license anymore. Therefore anyone could be driven in such cars alone. However, due to liability we restrict the age of driving alone to a certain age. In Germany children with the age of ten [17] are partly liable for their actions during the road traffic. Therefore, we set the minimum age of driving a autonomous vehicle to that age. The technical differences of the various automation levels include two main aspects: First, automated parking also known as valet-parking, which reduces the access and egress times to configurable constant times. The minimum automation level required for this feature can be freely configured as well. Second, a more pleasant time during riding. Currently we assume that the time during the ride is more pleasant due to the possibility to do something else or simply relax. Therefore, we use the approach presented in [18] [19] to simulate these effects: For a certain ramp-up time t_{ramp} we assume no positive effect, because the ride is simply too short. After this ramp-up time we apply a short-range reduction factor m_{short} of the remaining travel time. If the trip is longer than a specified threshold t_{long} we apply a second reduction factor m_{long} for this exceeding travel time.

$$tt(x) = \begin{cases} x, & \text{if } x <= t_{ramp} \\ t_{ramp} + (x - t_{ramp}) \cdot m_{short}, & \text{if } x > t_{ramp} \text{ and } x <= t_{long} \\ t_{ramp} + (x - t_{ramp}) \cdot m_{short} + (x - t_{long}) \cdot m_{long}, & \text{if } x > t_{long} \end{cases} \tag{1}$$

The result of this approach is a perceived travel time of this trip with an autonomous car displayed in Equation 1, which is used in the cost-function for the mode choice model described in [11]. Doing so, the real driving time may differ from the perceived one. Therefore, we use real time for computing departure and arrival times of the trip but not for the mode choice.

Currently there is no indication that speed limits for automated cars will be different than for conventional cars. However, the safety margin between autonomous cars can be affected, since computers can react to emergency breaks much faster than humans. This will lead to a reduction of the time gap between consecutive driving cars. The reduced time gap between vehicles and the resulting adjustment of road capacity play an important role in routing of self-driving cars. Modeling of vehicle behavior in SUMO can be done either with a time discrete but spatially continuous microscopic car following model (which by default uses the model developed by Stefan Krauss) or with an event-based mesoscopic model. Both approaches are used for the study area, microscopic for detailed urban simulations such as for the city of Brunswick and mesoscopic if the whole area with all motorways is simulated. The reason for choosing mesoscopic simulation is mainly due to the size of the study area and the speed of execution. SUMO allows individual setting of model parameters for each vehicle in both models. In this way, it is possible to set a smaller time gap or reduce the maximum speed for automated vehicles. To account for the fact that automated vehicles may generally drive in shorter distances (even in slow or standing traffic), the minimum (space) gap can also be adjusted, which has essentially the same effect as a reduced vehicle length. It is also possible to adjust the models so that the distance also depends on the type of vehicle ahead (e.g., have automated vehicles close only if they are behind another automated vehicle). This model adjustment requires external control, which slows down the simulation considerably and therefore was not used here. A resulting effect of the modified parameters is a change in the road capacity. The following approximate values, as shown in Table 1, are obtained in a mesoscopic SUMO simulation if the time gap is set to 1.15s for conventional and 0.5s for automated vehicles. It can be seen that on faster single-lane roads, the inhomogeneity caused by automated vehicles appears to cause a small drop in capacity at low penetration rates. This is a behavior of the model that (while not unrealistic) needs further investigation. The penetration rates used in this context refer to the upcoming scenarios.

Table 1: Road capacity in SUMO.

		Road capacity (vehicles/hour)			
Road type	Speed limit (km/h)	Conventional	Mix (18% automated)	Mix (44% automated)	Full Automation
highway (3 lanes)	140	5720	6160	6700	8060
federal road (1 lane)	100	2300	2230	2410	3200
country road (1 lane)	70	2160	2050	2270	2880
city road (1 lane)	50	1980	2050	2090	2520

3. Scenarios

The scenarios include both the reference case without automated vehicles and scenarios in which the penetration rate of fully automated vehicles varies. The scenarios cover the forecast year 2030. The underlying baseline scenario for the year 2017 is described in [20]. The population data from the base year were adjusted to the forecast year by using population projection data [21].

3.1. Reference scenario

The synthetic population of the REFERENCE scenario contains a total of 2.6 million persons grouped into 1.3 million households. This is an increase of about 6% compared to the baseline scenario. On average, 1.9 people live in each household. About 51% of all persons are female and the remaining are male. Approximately 16% of the inhabitants are younger than 18 years, 62% are of working age, and 22% are 65 years or older. Figure 2 presents the spatial distribution of the population density. In the study area there are almost 1.4 million privately owned cars available. The distribution of the vehicle fleet in terms of powertrain and car size is shown in Figure 3. The overall level of motorization is about 543 vehicles per 1,000 inhabitants. The number of cars and the belonging shares are based on the CAST [22] vehicle fleet model. This model provides data on the future development of the German passenger vehicle fleet.

3.2. Scenarios with fully automated vehicles

In order to measure the impact of privately owned automated vehicle on travel behavior, three possible scenarios have been created. First, the LIFELIKE scenario, which corresponds to a rather realistic assumption of 18% fully

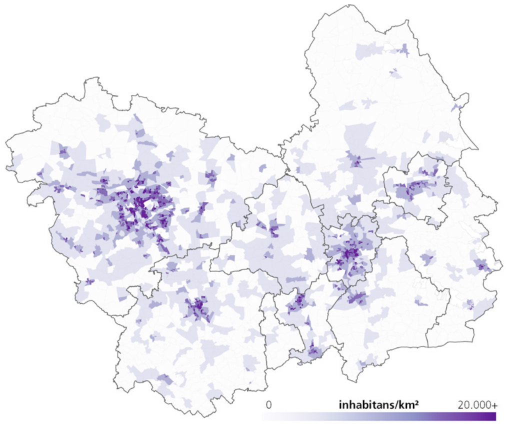

Fig. 2: Spatial distribution of the population density.

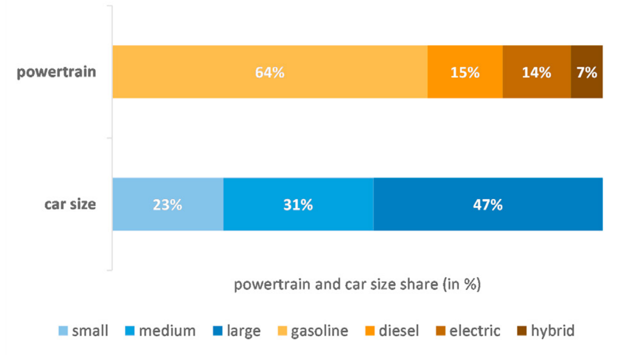

Fig. 3: Distribution of the vehicle fleet in terms of powertain and car size.

automated vehicles, whereas the PROMISING scenario with a share of 44% represents more like a optimistic view. Both scenarios refer to the assumptions developed in [23]. Here, the proportions for the study area are slightly higher than the underlying nationwide average. In addition, a HIGHTECH scenario have been set up, in which all privately owned vehicle drive autonomously. Depending on the penetration rate, the conventional cars were randomly replaced by self-driving cars. These fully automated vehicles can be used by any household member from the age of ten, even without a driver's license. Here, only people from households with own cars were taken into account. In addition, valet-parking is being considered for these vehicles. This means, that the time spent looking for a parking space is omitted because of the fact, that a self-driving car parks on their own. In other words, the trips made by self-driving cars are provided as a door-to-door service. Since no valid data was available for locating potential parking spaces, the additional car traffic resulting from empty trips to or from the parking lot is not simulated. However, this does not affect the comparability to trips made by conventional cars, since the distance traveled to find a parking space at the final destination is not modeled either. All scenarios are based on the REFERENCE scenario, but they differ in the penetration rate of fully automated vehicles. An overview of the implemented scenarios and their settings is shown in Table 2. Each scenario is computed only once. The stochastic deviation between different runs of the same scenario in TAPAS are negligible as shown in [14].

Table 2: Overview of implemented scenarios and their settings.

Features / Scenarios	REFERENCE	LIFELIKE	PROMISING	HIGHTECH
number of inhabitants		2.551.684		
number of households		1.331.932		
number of vehicles (privately owned)		1.373.485		
penetration rate (for self-driving cars)	0%	18%	44%	100%
valet-parking (for self-driving cars)	no	yes	yes	yes
new user groups (for self-driving cars)	no	yes	yes	yes

4. Results

About 8.8 million trips were simulated in each of the four scenarios, which represents the total traffic volume on a workday in the study area. A minor increase in the total traffic volume could be observed between the scenarios. The highest difference of about 1% can be seen between the REFERENCE and the HIGHTECH scenario. It should be mentioned, that there is already an increase in the number of trips of about 6% between the 2017 baseline scenario and the REFERENCE scenario. This is primarily due to the growing population in the study area by the forecast year 2030. The long-distance trips make up to 4% of the total traffic volume for each scenario. Long-distance trips are defined hereby as journeys with a trip length of at least 30 kilometers. There are more than 1.2 million working trips in total. About 5% of these trips belong to commuters. Commuters include in-commuters, which work in Brunswick but live outside the city and out-commuters who are living in the city but work outside of Brunswick. An overview of the simulated trips for all trip purposes is shown in Table 3, whereas the simulated working trips are presented in Table 4.

Table 3: Simulated trips for all trip purposes.

Trips for all purposes	REFERENCE	LIFELIKE	PROMISING	HIGHTECH
total traffic volume	8,769,792	8,793,385	8,835,495	8,875,288
long-distance (share of total traffic volume)	4%	4%	4%	4%

Table 4: Simulated working trips.

Working trips	REFERENCE	LIFELIKE	PROMISING	HIGHTECH
total traffic volume	1,200,539	1,206,535	1,214,694	1,223,805
commuter (share of total traffic volume)	5%	5%	5%	5%

The mode share for each simulated scenario including all trips is shown in Figure 4. It can be seen, that going by car has increased over the scenarios up to 5%. The increase in motorized individual transport has a negative impact on all other modes of transport. Car passengers and public transportation decrease the most, whereas walking and using a bike reduces only slightly. The shift towards more car usage can be explained by the new user groups. Because, these persons now have an additional option within the applied mode choice model. Figure 5 shows the daily mileage driven by car. Here, an increase of up to 9.3 million kilometers can be observed in the HIGHTECH scenario, which corresponds to an overall gain of approx. 21%. In both figures, the different proportion between the use of a conventional and an automated car is visible. It should be noted that the number of trips made by an automated vehicle does not directly reflect the share of these vehicles in the corresponding vehicle fleet. The proportion is significantly higher and could indicate a greater usage of these vehicles.

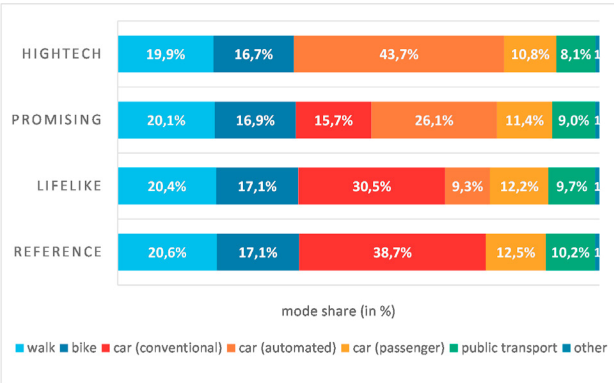

Fig. 4: Mode share for the simulated scenarios.

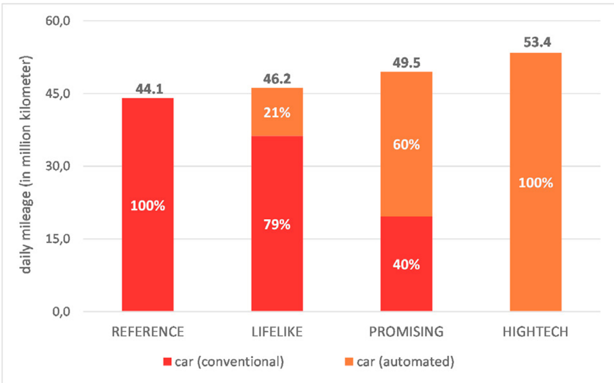

Fig. 5: Daily mileage of the motorized individual transport.

In the following, the motorized individual transport is analyzed in more detail. The evaluations of travel time and distance contain the respective average value for each scenario. In addition, the standard deviation (sd) is given for commuters. The median, on the other hand, is more meaningful for long-distance trips, as the distribution is skewed to the right due to the threshold of at least 30 kilometers of trip length. Table 5 shows, that the average travel time for autonomous vehicles decreases compared to conventional vehicles across all scenarios. The strongest reduction can be seen between the REFERENCE and HIGHTECH scenarios. Here, the average travel time is reduced by about 11 minutes for long-distance trips and 9 minutes for commuters. This corresponds to a saving of 26% respectively 27% of the average travel time. The major savings in travel time for autonomous vehicles are mainly based on an optimized traffic flow and on valet-parking, as this reduces the access and egress times. The LIFELIKE and PROMISING scenarios also show a reduction in travel time. However, this decrease is lower because both scenarios assume mixed traffic and therefore the advantages of self-driving cars are not realized completely.

Table 5: Average travel time for motorized individual transport trips.

Travel time (in minutes)	Conventional vehicles			Automated vehicles			Both vehicle types			
	REFERENCE	LIFELIKE	PROMISING	LIFELIKE	PROMISING	HIGHTECH	REFERENCE	LIFELIKE	PROMISING	HIGHTECH
long-distance (average/median)	43/33	43/33	43/34	34/26	32/25	32/25	43/33	41/33	37/30	32/25
commuter (average/sd)	33/25	30/21	30/19	30/23	25/19	24/18	33/25	30/22	28/19	24/18

The evaluation of the travel distance for the motorized individual transport is shown in Table 6. Long-distance trips are on average 43 kilometers long in the REFERENCE scenario and increases up to 45 kilometers in the HIGHTECH scenario. The average travel distance for commuters lies by 23 kilometers in the REFERENCE scenario and increases of up to 1 kilometer over the scenarios. This corresponds to an increase of the average travel distance by up to 5% for long-distance trips and 4% for commuters.

Table 6: Average travel distance for motorized individual transport trips.

Travel distance (in kilometer)	Conventional vehicles			Automated vehicles			Both vehicle types			
	REFERENCE	LIFELIKE	PROMISING	LIFELIKE	PROMISING	HIGHTECH	REFERENCE	LIFELIKE	PROMISING	HIGHTECH
long-distance (average/median)	43/38	44/38	44/39	45/39	44/38	45/39	43/38	44/38	44/39	45/39
commuter (average/sd)	23/16	22/15	22/15	27/17	25/16	24/16	23/16	23/16	24/16	24/16

5. Conclusion

This paper analyzed the impacts of using privately owned automated vehicles by simulation runs. The simulation environment focused on the region covering the Test Bed Lower Saxony in Germany as study area. Furthermore, it includes the agent-based demand model TAPAS and the traffic flow model SUMO, which are both available as open source. The paper introduces four scenarios with different penetration rates of fully automated vehicles. Additionally, it gives details on the implemented approaches used for simulating the impact of automated vehicles within the applied traffic models.

It could be shown that the introduction of automated vehicles will have a major impact on travel behavior. There has been a significant shift in the mode share towards more car usage of up to 5% as well as an increase in daily mileage driven by car of around 21%. This might be explained by the new user groups within the scenarios with self-driving cars. Here, it was assumed that all members of households with own cars would be able to use these independently, even without a driver's license starting at an age of ten. Therefore, these persons have an additional option within the mode choice model. The high growth of up to 5% in the mode share could be even stronger if people without an own car were also taken into account in relation with car-sharing offers. In addition, the average travel time and travel distance for long journeys as well as for commuters to and from the city of Brunswick were analysed in more details. Here, the average travel time is reduced by 26% for long-distance trips and up to 27% for commuter journeys. The major travel time savings for self-driving cars are primarily due to an optimized traffic flow as well as on valet-parking, as this reduces the access and egress times. Furthermore, a minor increase could be observed for the average travel distance. It should be mentioned that TAPAS does not include long-term effects such as the choice of residence or workplace. This could contribute to not seeing major changes in travel distance, especially for commuters.

Overall, the simulation results show that there is rather a shift within the mode share than an increase in travel demand. The traffic volume, which remains almost the same in the scenarios, might not be realistic and should therefore be investigated in more detail. In the current used mode choice model, the car is not available to other household members if it is already used for a main activity, e.g. commuting to work. Here, it is assumed that the car will also be used for the returning trip and therefore remains at the workplace location. In the case of self-driving cars, there is the possibility that they will drive back on its own if needed. The car could thus potentially be used for additional trips. Therefore, the implementation of the mode choice model within TAPAS have to be adapted accordingly. Switching from a household-based to a time-sequential approach during the simulation might be also helpful. However, it is highly possible that additional traffic caused by empty rides of automated vehicles will be regulated in the future.

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