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Working Paper

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Publication date:
2019-11

Permanent link:
https://doi.org/10.3929/ethz-b-000379742

Originally published in:
Arbeitsberichte Verkehrs- und Raumplanung 1472

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Abstract

Automated vehicles are widely expected to bring about various benefits for (urban) transportation, e.g. by increasing road capacities and reducing generalized cost of travel. However, the latter may induce additional demand for road transportation, possibly counteracting gains in accessibility. Hence, the net impact of vehicle automation on road network performance is still unclear. This research uses the macroscopic fundamental diagram (MFD) to address this question for different levels of road capacity increases and modal splits between private and shared (i.e. public) transportation. To this end, various scenarios are tested in a simulation model for the morning peak hour for Zurich, Switzerland, as a case study, for which current demand levels for car and public transport are used. Yet, the results can be generalized to different city types. The analysis indicates that for car-oriented cities, vehicle automation will likely bring substantial benefits in network performance, while for public transport oriented cities, substantial gains in road capacity of 40 % or more will be required to make up for the potentially substantial mode shift from public transport towards (pooled) cars. Moreover, results show that up to 75 % mode share of ride-sharing trips will be required to achieve a system-optimal state.

Keywords

self-driving vehicles, automated vehicles, macroscopic fundamental diagram, MFD, congestion, capacity

Suggested Citation

H. Becker, A. Loder and K. W. Axhausen (2019) Will automated vehicles help to reduce congestion?, *Arbeitsbericht Verkehrs- und Raumplanung*, **1472**, IVT, ETH Zürich.

1 Introduction

Vehicle automation is widely expected to bring about large benefits for urban transportation, for example by making roads safer (Fagnant and Kockelman, 2015), by reducing costs of travel (Bösch *et al.*, 2018) and by potentially allowing a more sustainable transport system (Wadud *et al.*, 2016). Through operation as shared and/or pooled services, existing infrastructure and resources could be used even more efficiently (Cervero, 2017). However, such benefits may also induce changes in travel demand, potentially counteracting the expected positive impacts (Meyer *et al.*, 2017; Metz, 2008). At the same time, it is unclear how automation technology will impact urban road capacities (Le Vine *et al.*, 2015). Hence, the question arises, how the obvious benefits can be harnessed, while staying within the physical capacity limits of the urban transport network.

Since the mechanisms of traffic flow are generally understood (Daganzo, 1994; Nagel and Schreckenberg, 1992), the above question can be broken down into assessing the respective parameter changes due to automation. In particular for road and intersection capacity, various such assessments already exist (Tientrakool *et al.*, 2011; Le Vine *et al.*, 2015; Friedrich, 2016). Yet, these factors alone do not allow to estimate the effects of automation on the possible productivity of existing urban infrastructures (i.e. the number of completed trips in a network (Daganzo, 2007)), since characteristics of demand may also change. The theory of the macroscopic fundamental diagram (MFD) provides a link between physical limits and productivity of urban networks (Daganzo, 2007; Loder *et al.*, 2019a) and thus allows to analyze the impact of vehicle automation on network performance. The MFD abstracts urban road networks into a bathtub-like (Arnott, 2013) reservoir with inflow, internal flow and outflow, where the two latter flows depend on the vehicle accumulation inside the reservoir.

In general, vehicle automation can be expected to affect network performance in two ways: It may increase road capacity through smoother driving and a shorter minimum headway. However, since automated vehicles are largely expected to operate as (pooled) taxis, they will also be moving bottlenecks (when stopping to allow passengers to board or alight) and induce higher vehicle miles travelled (VMT) through detours (if rides are pooled) and empty travel. Hence, the net impact will depend on the relative strength of the two effects.

This paper presents a first discussion on how automation of vehicles and their operation as individual or pooled service can improve the productivity of urban transport networks.

We consider only two road surface modes: private automated taxis and pooled automated taxis[1]. For each mode, corresponding MFDs are defined for the downtown area of Zurich, Switzerland, which are then used to simulate a typical morning commute in a simplified model which does however not capture complex reservoir dynamics (Mariotte *et al.*, 2017; Aghamohammadi and Laval, 2018). Scenarios with varying market shares of the different services are considered.

The remainder of the paper is organized as follows. In Section 2, earlier research on vehicle automation is discussed. Section 3 introduces the MFD and the relevant parameter changes to adapt it to (shared-) autonomous operations. Thereafter, we introduce in Section 4 the model used in this paper before showing the scenario analysis in Section 7. The results are discussed in Section 8, while Section 9 shows the practical implications of this research.

2 Impacts of vehicle automation and sharing

Automated driving technology (full automation (level 5) as defined by SAE International (2014)) will likely trigger substantial disruptions in both transport demand and supply. By driving production costs of taxi services down to a level comparable with public bus services (Bösch *et al.*, 2018), such automated taxis will likely become a relevant mode of transportation, potentially substituting formal line-based public transport services, at least in lower-density environments. Also private vehicles will become more attractive when automated (Daziano *et al.*, 2017) as they may provide features of a personal chauffeur and errand boy.

Assuming a static demand, earlier research has shown that switching all car travel to automated taxis would allow to slash required fleet sizes by up to 90 % (Bösch *et al.*, 2016). In addition, it was found that 15 % of New York's current taxi fleet would be sufficient to serve all taxi trips, if rides were shared by multiple passengers (pooled taxis) (Alonso-Mora *et al.*, 2017). But through empty travel in an automated taxi scheme, total VMT would increase by 10 % (Fagnant and Kockelman, 2014), whereas for pooled trips, detours are required to cover the origins and destinations of all passengers (3.5 min in the study by Alonso-Mora *et al.* (2017)). Yet, the assumption of a static demand is unrealistic. Not only will cheap automated taxis change the accessibility landscape

[1] The latter category may also include buses if defined as such.

and thus land-use patterns, they will also attract new user groups for road transport (Meyer *et al.*, 2017), thus substantially changing origin-destination relations and increasing demand. In addition, increasing urbanization in the future will add more pressure to urban transportation systems (Schafer and Victor, 2000).

Vehicle automation will also have profound impacts on traffic flow characteristics: Faster reaction times of sensors will allow shorter headways and thus an increased road capacity. Benefits can be increased further by vehicle-to-vehicle communications allowing smoother driving and even shorter headways (Tientrakool *et al.*, 2011; Friedrich, 2016). As a result, also stability of traffic flow will be higher (Talebpour and Mahmassani, 2016). However, such analyses have mostly been done for highway traffic so far (Fountoulakis *et al.*, 2017) and only rarely took into account legal standards of care, which may however limit the possible capacity gains (Le Vine *et al.*, 2017). For urban road networks, capacity is mostly determined by intersection capacities (Transportation Research Board, 2016). However, there is no agreement on the impacts of vehicle automation yet. While Fajardo *et al.* (2011) and Li *et al.* (2014) predict increases in throughput of up to 20 %, Le Vine *et al.* (2015) even find a decrease in capacity, when restricting lateral accelerations to a level considered comfortable for passengers. In a highly integrated regime, removal of traffic lights may allow even more efficient operations (Kamal *et al.*, 2015), at the expense of cyclists and pedestrians.

A further way to increase road capacity may be achieved by vehicle right-sizing, i.e. by designing smaller, purpose-built vehicles. Also, policies such as speed limits may be adjusted in the light of increased traffic safety.

Since automated vehicles will likely be used like today's taxis, they will drop off passengers as close to their destination as possible (and the same for pick-up), thus blocking a lane during this dwell time unless dedicated infrastructure will be provided. This is similar to buses, where the impact on performance has already been intensely studied (Eichler and Daganzo, 2006; Nagai *et al.*, 2005; Castrillon and Laval, 2018). For ride-hailing services, earlier research suggests that this effect (along with empty VMT) already causes substantial losses in network speeds (Schaller, 2017). However, the resulting impact might be different if automated vehicles were in play.

This research aims to combine insights on trip characteristics and traffic flow parameters in a future regime of automated taxis to study their impact on transport network performance using the macroscopic fundamental diagram (MFD). The focus of this study lies on full vehicle automation (level 5 (SAE International, 2014)), acknowledging that a potential implementation of fully connected vehicles may allow further capacity benefits (Tientrakool *et al.*, 2011) in the distant future.

3 The MFD and vehicle automation

The underlying idea of the MFD is to think of urban networks as a *bathtub* or reservoir (Daganzo, 2007; Arnott, 2013). All microscopic or local between-vehicle interactions affecting network performance are not explicitly considered anymore, but implicitly accounted for in the relationship between reservoir accumulation and reservoir outflow, the MFD (Geroliminis and Daganzo, 2008). The MFD shape depends only on road network structure, signal settings, route choice and the fundamental diagram (Daganzo and Geroliminis, 2008; Laval and Castrillón, 2015; Leclercq and Geroliminis, 2013). We assume that the effects of vehicle automation can be expressed in four basic parameters of the fundamental diagram: free-flow speed, saturation flow, jam density and backward wave speed.

Using results of earlier research and own assumptions, estimates for the respective parameter changes were obtained. In essence, it is assumed that the free-flow speed u_f is only slightly increased because of the general political trend to limit or lower speeds within cities (c.f. Kockelman *et al.* (2017)). Saturation flow is increased by 40 % and 78 % as suggested by Friedrich (2016) (Talebpour and Mahmassani (2016) even expect increases of 100 % on specific roadway settings). With only minor changes in vehicles sizes, the jam density K_{jam} is expected to increase only marginally (c.f. Kockelman *et al.* (2017)). Due to better reaction times, the backward wave speed w could also improve as the reaction time decreases. However, too fast reaction times could trigger motion sickness. Here, the backward wave speed w is derived from the above variables using

$$w = \frac{q_{sat}}{K_{jam} - K_{crit}} \tag{1}$$

where

$$K_{crit} = \frac{q_{sat}}{u_f}, \quad q_{sat} = s \cdot G/C. \tag{2}$$

Table 1 – Comparison of trapezoidal MFD parameters

	Unit	Conventional car	Full automation	Source
Free-flow speed u_f	[km/h]	25 - 30	30 - 35	Kockelman *et al.* (2017)
Jam density K_{jam}	[veh/lane-km]	130 - 160	140 - 170	Kockelman *et al.* (2017)
Saturation flow s	[veh/h-lane]	1 500 - 1 700	2 650 - 3 050	Friedrich (2016)
Green time ratio G/C	[-]	0.4	0.4	own assumption
Wave speed w	[km/h]	5.0 - 5.7	9.0 - 10.1	follows from K_{jam}, s and u_f
Capacity Q	[veh/h-lane]	600 - 680	1 060 - 1 220	follows from s and G/C

The resulting MFD parameters are presented in Table 1, where they are also compared to current MFD parameters for the city of Zurich (Loder *et al.*, 2017). The table also contains assumptions on two relevant network attributes: Green time ratio and capacity. In an urban setting, the former is assumed unchanged to still be able to accommodate pedestrians and cyclists (Millard-Ball, 2018). Furthermore, we assume that network structure (extent of the network and routing) will likely remain unchanged, so that the realized capacity Q typically follows from the product of saturation flow and average green time ratio (Daganzo and Geroliminis, 2008).

It is assumed that the parameters defined in Table 1 are valid for both individual automated taxis and pooled taxis, with the exception of the speed value: Pooled vehicles usually have to stop at a distance d for boarding and alighting passengers where the vehicle stops for time τ. Hence, the average commercial free flow speed speed of pooled vehicles is adjusted to

$$v_{shared} = \frac{d}{d/u_f + \tau}. \tag{3}$$

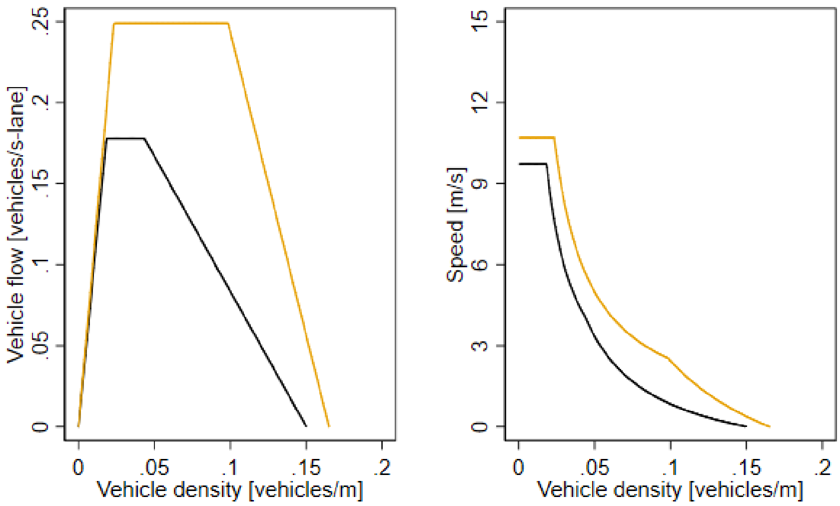
In this research, the MFD is simplified to a trapezoidal shape (Daganzo *et al.*, 2017) as given by:

$$q(k) = \min\left(u_f k; Q; \left(K_{jam} - k\right) w\right). \tag{4}$$

To obtain a smooth and concave shape of Equation 4, we use the smooth approximation proposed by Ambühl *et al.* (2018). Figure 1 presents the resulting trapezoidal shape of the MFD for conventional cars (black line) and automated cars (orange line) using the average of parameters from Table 1. Thus, the figure summarizes the effects of vehicle automation on the MFD.

In application contexts, the MFD faces several important caveats such as heterogeneity in

Figure 1 – A typical MFD for urban traffic with conventional car vehicles (black) and automated vehicles (yellow).



the distribution of traffic (Ji and Geroliminis, 2012; Saeedmanesh and Geroliminis, 2016) or accounting for the dynamic effects of loading and unloading the network (Gayah and Daganzo, 2011; Daganzo *et al.*, 2011), both of which lead to an inaccurate and biased MFD estimates. In this analysis, however, we do not address these effects as we want to understand traffic performance in an optimal case for long-term planning purposes.

4 Methodology

We investigate the influence of vehicle automation and shared ride systems on the performance of urban road networks using a simulation of a simplified MFD-based *bathtub*-model (Arnott, 2013; Mariotte *et al.*, 2017). In the present analysis, we model the morning peak for two main reasons. First, the morning peak usually demands the full capacity of the network. Second, it has the pleasant boundary constraint of an empty network at the beginning of the analysis horizon.

In general, the simulation calculates traffic states minute-by-minute from 6 am to 10 am for an assumed exogenous and static travel demand. Mode choice is not modeled explicitly as we want to understand how the performance of the system varies when the demand is distributed by experimental design over private automated taxis and pooled automated taxis. Thus, a fixed modal split between private (ψ) and pooled ($1-\psi$) automated taxis is defined.

In the simulation, we expect zero interaction costs between private and pooled automated taxis. This means they do not create any negative externalities to vehicles of the other mode, but only within each class of automated taxi, because we assume that each mode runs on dedicated infrastructure, i.e. designated lanes. This kind of lane separation already exists in form of dedicated bus lanes or HOV lanes on motorways. The share of the network for private taxis is η and $1-\eta$ for pooled taxis. As emphasized before, we want to understand the optimal traffic outcome that can be possible or an upper bound of the performance. However, in reality, substantial interactions would have to be expected (at least at intersections), and thus decrease performance.

Consequently, the two main experimental variables of the model are the division of demand among private and pooled taxis, ψ, as well as the division of infrastructure among private and pooled taxis, η. The two assumptions of static and exogenous demand as well as zero interaction costs mean that each mode is modelled in its own reservoir and MFD.

Mathematically, we define the speed as a function of the number of vehicles N within each reservoir by Eqn. 5, a recently introduced functional form for the MFD (Ambühl *et al.*, 2018). Here, u_f, Q, w, and K_{jam} are as defined in Table 1, while λ is a smoothing parameter set to be around 0.02 for conventional vehicles. For automated vehicles, λ is assumed 75 % lower due to lower expected losses through vehicle interactions. Finally, L is the total length of infrastructure. As the following two equations hold for private and pooled automated taxis in the same way, we omit for readability the corresponding indices.

$$v(N) = -\lambda \ln\left(\exp\left(-\frac{u_f(N/L)}{\lambda}\right) + \exp\left(-\frac{Q}{\lambda}\right) + \exp\left(-\frac{\left(K_{jam} - (N/L)\right) w}{\lambda}\right)\right) / (N/L) \tag{5}$$

With known speed $v(N)$ and trip length l we can now determine the travel time T by Eqn. 6.

$$T = \frac{l}{v(N)} \tag{6}$$

In each interval t, the network - or reservoir - experiences an inflow of vehicles of q_{in} and outflow of vehicles q_{out}. When vehicles enter or leave the network, the accumulation of vehicles N changes and as given by Eqn. 5 the network average space-mean speed in the MFD also changes. We define the accumulation of vehicles N as the number of cars which have not yet finished their trip after driving for a distance l.

In the simulation, we assign all vehicles entering at interval t the network average speed $v(N)$ based on the current accumulation of vehicles at time t when they enter the network. The vehicles stay in the reservoir at this constant speed until they finished their trip. Although this assumption might be rather simplistic, we consider information loss to be marginal as demand is changing only slowly. Furthermore, if using the precise speed information in each simulation step, the simulation also has to account for the fact that the information of speed change cannot travel faster than the vehicles and is not instantaneous. This is a non-trivial task (Mariotte *et al.*, 2017).

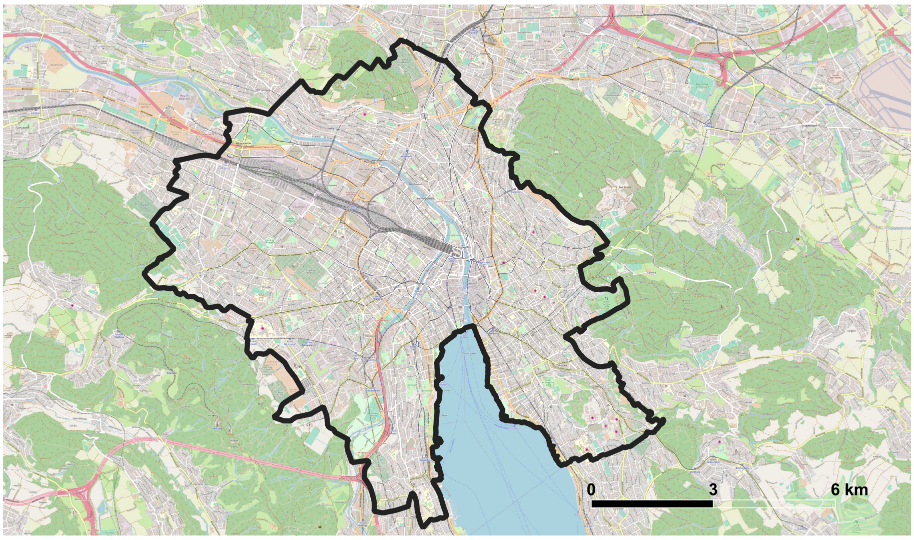
Lastly, we assume that private automated taxis are only occupied by one passenger, while pooled automated taxis can carry more passengers, on average ρ persons per vehicle. In the simulation, we consider that the number of vehicles is not restricted, i.e. all passengers will be assigned to vehicles. However, we define that passengers *miss* their trip once the network is at grid lock, i.e. K_{jam}, preventing them from entering the network.

5 Case study: Zürich

We analyze the effects for the city center of Zurich, Switzerland, as shown in Figure 2. The city of Zurich has 425 000 inhabitants (1.3 million in the metropolitan area). With 360 000 jobs located in the city, there is a substantial inflow of commuters each morning. Zurich residents frequently travel on active modes (i.e. walk or bike), 32 % of the trips are done using public transportation, 25 % using private cars. Overall, 24 % of the settlement area are devoted to transportation infrastructure. For the given perimeter, we define the traffic model parameters as given in Table 2. Data on the transportation network as well as current travel demand data was available from the official macroscopic assignment model of the Canton of Zurich (Vrtic *et al.*, 2015).

As discussed above, vehicle automation and the corresponding new service types will also affect demand characteristics (Eqn. 3). Dwell time τ was measured at the passenger

Figure 2 – Study area.



drop-off area at Zurich airport. For ride-hailing or taxi vehicles dropping off passengers without heavy luggage, average time between arrival of the vehicle and continuation of the drive was 30 seconds. Hence, total dwell time per passenger is $\tau = 1$ min (30 s boarding plus 30 s alighting). The average trip distance l_i was obtained from the Swiss national household travel survey (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012), which indicates an average of 3.4 km for car trips within the city of Zurich (Bösch *et al.*, 2018). For pooled trips an additional dwell time of 1 min is assumed (two pick-up or drop-off activities). Given an acceptable additional travel time of 3.5 min (Alonso-Mora *et al.*, 2017), the remaining 2.5 min of travel time translate into a 25 % higher trip distance for pooled trips (at 20 km/h average network speed). For pooled trips, vehicle occupancy ρ was assumed 2.6 passengers (in accordance with Bösch *et al.* (2018)).

As we model the morning peak for Zurich, we obtain the exogenous departure rate distribution from the Swiss national household travel survey 2015 for Zurich from 6 am to 10 am (Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE), 2012). We find that the departure rate distributions fit gamma distributions, which scaled to the totals for car and public transport from the Cantonal traffic assignment model Vrtic *et al.* (2015), is presented in Figure 3. The total inflow is q_{in} = 35 100 vehicles and 69 800 public transport trips (7am to 8am). Scaled up to the

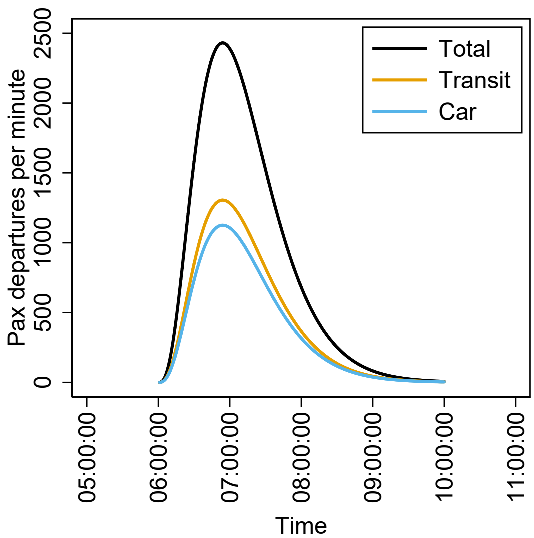
[2] AV numbers in this table assuming 80 % capacity increase. Values are adapted for the other cases correspondingly.

[3] It is assumed that 65 % of the infrastructure is actually available for traffic (compare Miller (1970)).

Table 2 – Summary of parameters used in the model. Details on the impact of vehicle automation are presented in Table 1.

Parameter	Unit	Conventional vehicles	Private AV	Pooled AV
Free-flow speed	km h^{-1}	27.5	32.5	28.8
Jam density	vehicles lane-km^{-1}	145	155	155
Backward wave speed [1]	km h^{-1}	5.3	9.5	9.9
Capacity [2]	vehicles h^{-1} lane^{-1}	640	1140	910
λ	(-)	0.025	0.020	0.020
Trip length	km	3.40	3.40	4.25
Additional dwell time	s	-	-	60
Infrastructure length [3]	lane-km	396 (road network) + 50 (bus/tram lanes)		

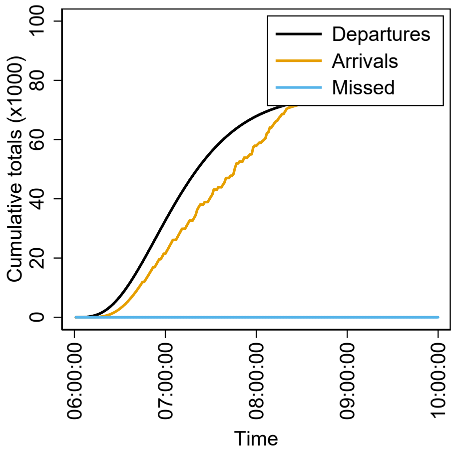
Figure 3 – Total departures and per means of transportation (based on Vrtic *et al.* (2015) and Swiss Federal Statistical Office (BFS) and Swiss Federal Office for Spatial Development (ARE) (2012)).



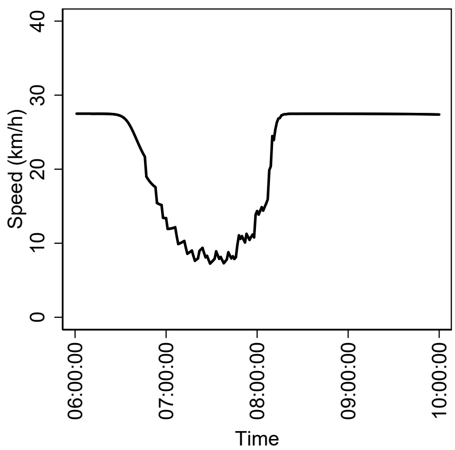
whole morning commute (6 am to 9 am) and also including outbound traffic, this results in a total travel demand of q_{tot} = 240 100 trips.

To validate the model calibration, we show in Figure 4 the model results for the current situation for conventional cars. The model results match closely the observed patterns from empirical observations in Zurich (Loder *et al.*, 2017). We do not show the model results for the public transport system because the decrease in commercial speeds and thus congestion is negligible.

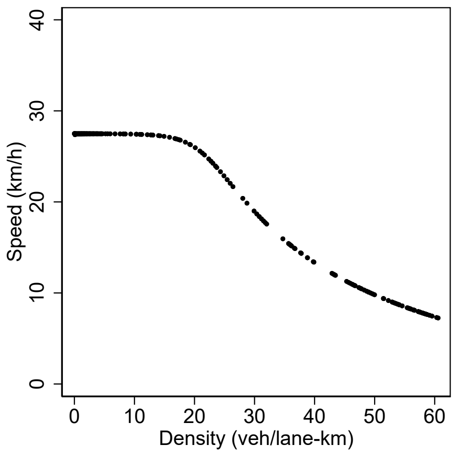
Figure 4 – The morning commute for conventional private vehicles for the calibrated model.



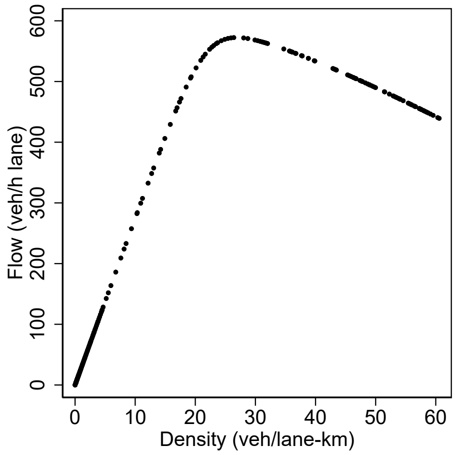
(a) a



(b) b



(c) c



(d) d

In detail, we find in Figure 4(a) that no car driver misses his or her trip and that the largest accumulation of vehicles is observed between 7 am and 8 am. We further see that the speeds in Figure 4(b) drop substantially and are close to 10 km/h. Recall that this is the average space-mean speed. The MFDs in Figures 4(c) and 4(d) clearly show that these traffic conditions are indeed in the congested regime. As a consequence, shifting some of the demand to other departure times or modes of transportation would allow the road network to operate at capacity, benefiting all car drivers.

6 Scenario analysis

The impacts of vehicle automation will likely be different for different types of cities. To capture part of this variance, two cases are studied:

- **Case 1:** all trips currently made by private cars will be covered either by private automated taxis or pooled automated taxis (i.e. taxis with ride-sharing). They are routed on the available car network (infrastructure) only. This case represents cities, which already have a very high share of car traffic (like many U.S. cities).
- **Case 2:** all street-bound public transport trips (i.e. buses and trams) will also be done by private automated taxis or pooled automated taxis. Available infrastructure includes both the car network as well as lanes currently dedicated to buses or trams. This case acknowledges that given the substantially reduced prices of (pooled) taxi services (Bösch *et al.*, 2018), they will likely attract public transport users. By assuming a 100 % mode shift, it represents an extreme case for a city with a highly-developed public transport system (like Zurich and many European cities).

Additional demand by new user groups or induced demand by lower generalized cost of travel are neglected in both cases (compare Meyer *et al.* (2017)). In this sense, together with omitting between-mode interactions on the roads, the results of this analysis can be regarded as best-case scenarios or upper bound estimate to traffic performance. Therefore, the actual future network performance may likely be worse.

To capture the current uncertainty in both impact on road capacity as well as the operational implementation of automated vehicles, a number of different scenarios was analyzed for each case. Scenarios were defined as combinations of three key parameters (also shown in Table 1):

- Impact of vehicle automation on road capacity. Although first estimates are available (Friedrich, 2016), there still is substantial uncertainty (Le Vine *et al.*, 2015, 2017). Hence, three levels (no change, 40 % increase (Friedrich, 2016) and 80 % increase) covering the most likely outcomes are considered.
- Share of trips conducted with private automated vehicles (vs. shared automated taxis) - from 0 to 100 %.
- Share of infrastructure devoted to private cars (vs. pooled automated taxis). For computational reasons, the two modes are assumed to travel on separate infrastructures. A practical interpretation would be the passing lanes for pooled taxis similar

Table 3 – Parameters and their levels

	Parameter	Levels		
γ	Capacity impact of automation	0 %	+40 %	+80 %
ψ	Share of demand for private transport	0 %, 5 %, 10 %, ... 100 %		
η	Share of network for private transport	1/3	1/2	2/3

to today's HOV lanes on highways in the United States.

The dimensions of the different scenarios are summarized in Table 3. All scenarios were then simulated in the model and analyzed with respect to the resulting network productivity as measured in lowest space mean speed observed during the morning peak.

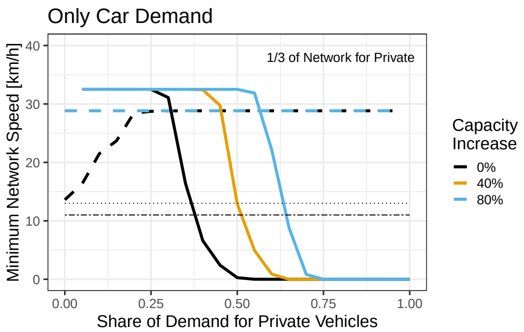
7 Results

All scenarios were simulated in the model for both the current car demand (case 1) and the total road surface transport demand (case 2). The most relevant outcome is the network speeds. Figure 5 presents the minimum average network speeds for the two modes between 7 am and 8 am and compares them to today's average network speeds of cars and tramways in the city center during that time.

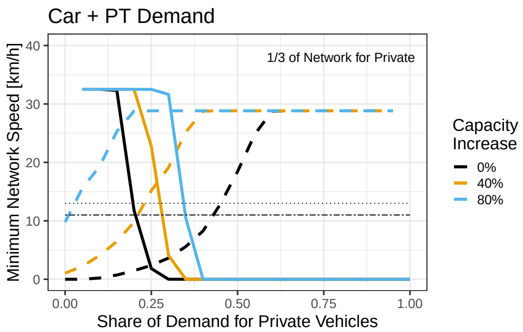
The results indicate that, naturally, maximum speeds are higher for private than for pooled vehicles (because of the additional dwell times). Moreover, when a higher share of demand is assigned to private vehicles (taxis), speeds for private vehicles drop and vice versa. Moreover, changes in the split of the network available for the two modes shift the curves to the left or the right. In general, the highest minimum speeds for both modes are achieved when the capacity split equals the split of demand for the two modes.

A key insight from Figure 5 can be taken from a comparison with current car and tram speeds. For a static car demand (only today's car trips), almost all scenarios suggest substantial improvements in network performance (up to doubling of speeds), partly because of a more efficient use of vehicles (through pooling) and partly through potential capacity benefits of vehicle automation. However, the outcome is less clear when considering the full demand (car plus street-bound public transport). Hence, the latter

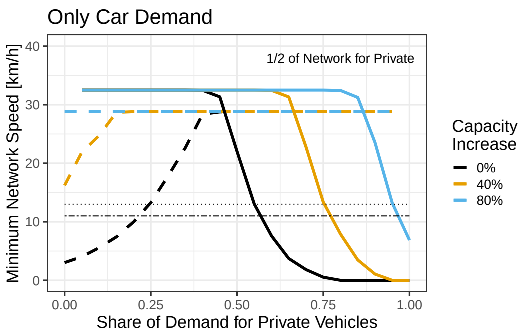
Figure 5 – Minimum network speeds for shared taxis (dashed) and private vehicles (solid). The dotted line provides the current network speeds of trams (13 km/h) as a reference; dash-dotted is the current speed of private cars during peak hour (11 km/h).



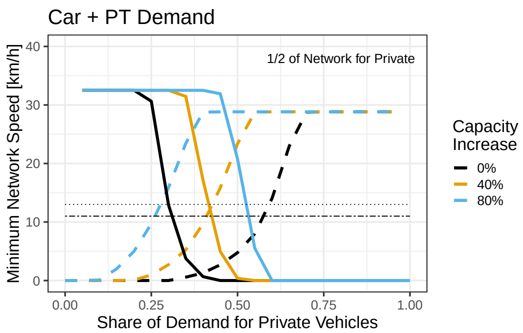
(a) 1/3 of network available for private vehicles.



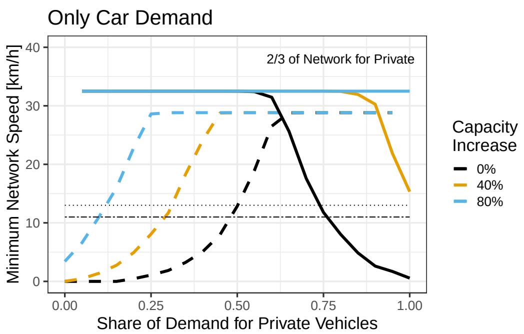
(b) 1/3 of network available for private vehicles.



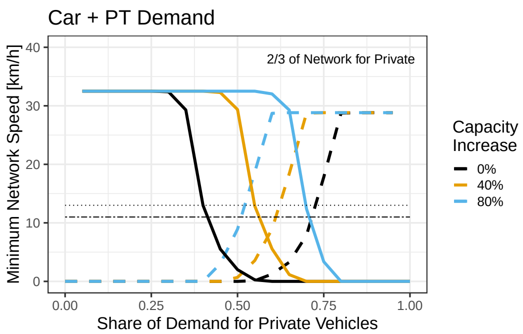
(c) 1/2 of network available for private vehicles.



(d) 1/2 of network available for private vehicles.



(e) 2/3 of network available for private vehicles.



(f) 2/3 of network available for private vehicles.

case has to be studied in more detail. In fact, Figure 5 indicates that only at an 80 % capacity increase, the road network would be able to cover the whole current travel demand (assuming zero induced demand) and still improve the level of service. In the more likely case of a 40 % capacity increase through automation, network speeds for both modes would remain on the level of today's private cars. Without any capacity increase, minimum network speeds would plummet to below 5 km/h (65 % decrease) with probably substantial implications on land prices and social welfare. Hence, future network performance will strongly depend on the capacity gains achievable by vehicle automation.

Yet, for network performance, not only the minimum speeds are important, but also the evolution of average network speeds throughout the study period. In Figure 6 network speeds are presented for the case of $\eta = 1/2$ and demand share for private vehicles $\psi = \{30\,\%, 50\,\%\}$.[4] The plots can be compared to the current situation shown in Figure 4. In the current case without vehicle automation, speeds decrease from 30 km/h at 6.30 am to 11 km/h around 7.30 am, but recover soon to reach the 27 km/h level soon after 8.00 am.

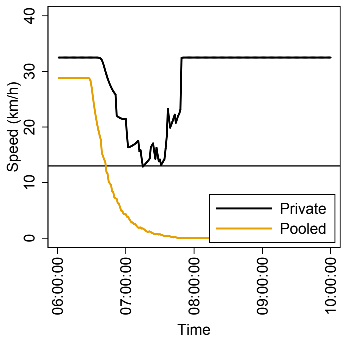
As shown in the first column in Figure 6, shifting all road-surface transport demand of today towards (pooled) automated taxis without any capacity gains results in a substantial loss in network performance. In particular, speeds plummet below current minimum speeds and take much longer to recover. Since road infrastructure dedicated to public transport today is also considered available for the two modes in the simulation (in the form of lane-km), this means that buses and trams cannot be simply replaced by pooled taxis without increases in road capacity through automation.

In the second column, speed distributions are shown for a 40 % capacity gain through automation. While the results approach the current situation (especially in Figure 6(d)), minimum speeds are still lower than today and also recovery after the peak hour takes slightly more time. However, given that the automated modes can be assumed more comfortable than driving a car or sitting in a bus, this situation may already constitute a general improvement compared to today. Yet, only with an increase of 80 % (third column), substantial efficiency gains can be expected.

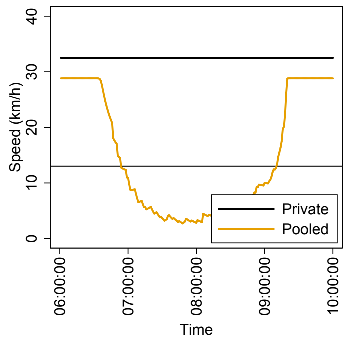
In addition, the simulation results can provide first insights on a favourable modal split between private automated cars and pooled automated taxis. To this end, the total travel

[4]In all plots, the full road surface transport demand is analyzed (case 2).

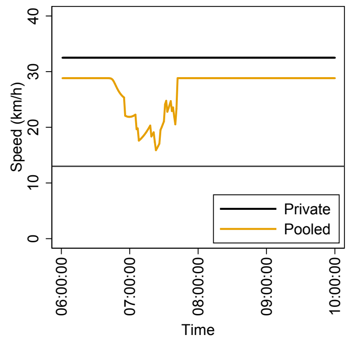
Figure 6 – Network speeds for pooled taxis (brown) and private taxis (black). The tremor in the curves can be explained by the discrete simulation steps and the fact that vehicles may leave the network in platoons.



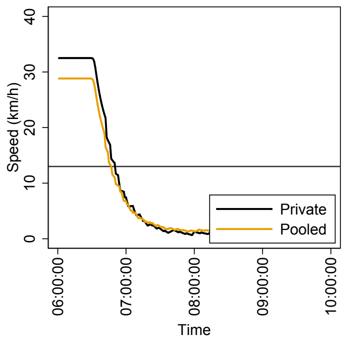
(a) γ = 0 %, η = 1/2, ψ = 30 %



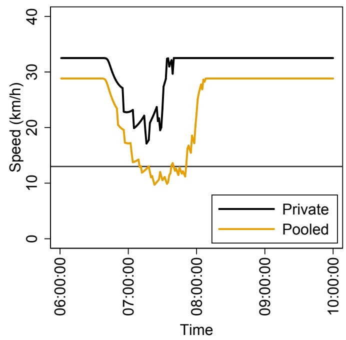
(b) γ = +40 %, η = 1/2, ψ = 30 %



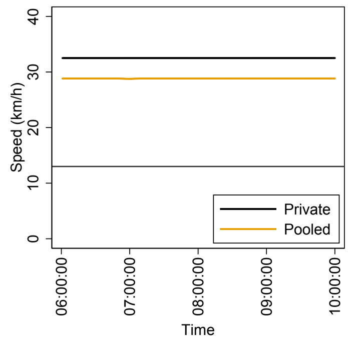
(c) γ = +80 %, η = 1/2, ψ = 30 %



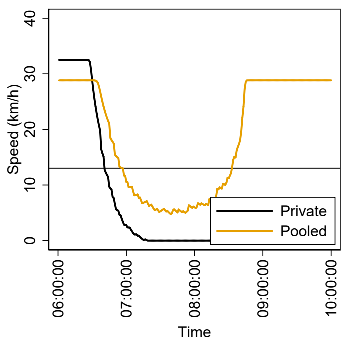
(d) γ = 0 %, η = 1/2, ψ = 40 %



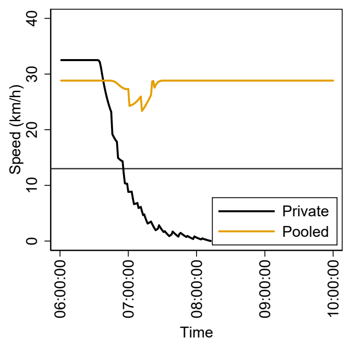
(e) γ = +40 %, η = 1/2, ψ = 40 %



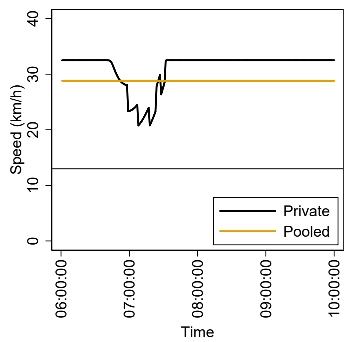
(f) γ = +80 %, η = 1/2, ψ = 40 %



(g) γ = 0 %, η = 1/2, ψ = 50 %

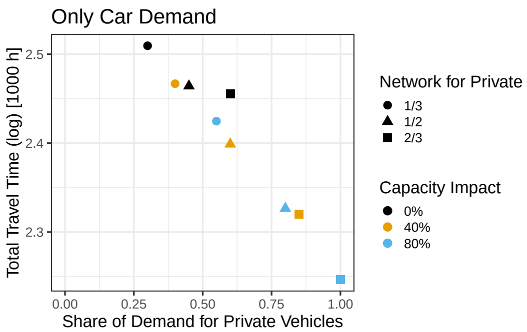


(h) γ = +40 %, η = 1/2, ψ = 50 %

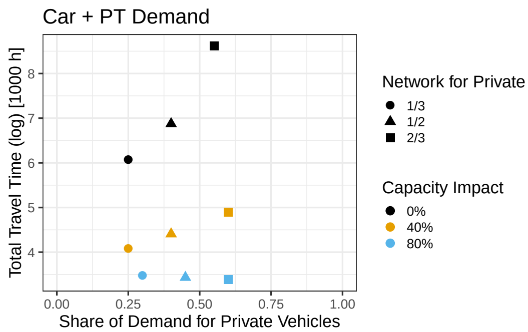


(i) γ = +80 %, η = 1/2, ψ = 50 %

Figure 7 – Minimum of total travel times (log) for the different scenarios.



(a) Only car demand



(b) Car + PT demand

times were calculated for each scenario. For the purpose of this first analysis, it is assumed that the system-optimal case corresponds to the case with minimum total travel time. In reality, disparities in values of time may translate into cases with higher shares of private modes being system-optimal. The results of this first analysis are presented in Figure 7.

As a first insight, the optimal mode share of private vehicles depends on the capacity impact of automation: because pooled automated taxis need to stop more often for pick-up and drop-offs, they benefit less from capacity gains (and hence, speed increases) than private taxis. In addition, it depends on the share of infrastructure available for this mode. However, in reality the same road infrastructure will likely be shared between private automated and pooled automated vehicles.

Hence, most informative is the global minimum of total travel times. When considering only today's car demand and no capacity gain through automation, a 60 % mode share of private vehicle trips (vs. 40 % shared rides) would be optimal. Assuming an 80 % capacity gain, the optimum would move to 100 % private trips. Interestingly, the results are substantially different for the case of the full road-surface transport demand (car plus public transport): Here, minimal total travel times are reached at a private vehicle mode share of 25 % - 30 % for a 0-40 % capacity increase. Only for an 80 % capacity increase, a 60 % mode share for private trips is travel time optimal.

8 Discussion

Today's urban road networks are jointly used by fast-driving cars and slower buses and trams, which need to stop frequently to allow passengers to board and alight. Due to this behavior, such public transport vehicles represent moving bottlenecks (Eichler and Daganzo, 2006; Castrillon and Laval, 2018). In an era of automated vehicles, public transport services and private cars will likely be complemented and at least partially be replaced by (pooled) automated taxis. Yet, both kinds of automated taxi services can be expected to frequently drop off and pick up passengers at the curbside, thus becoming moving bottlenecks in the network, too. Hence, the nature of mixed traffic with faster non-stopping vehicles and vehicles frequently stopping at the curbside will not change. In a way, the results can even be generalized to automated vehicles in private possession since they can also be expected to perform pick-up and drop-off activities at the curb. Future research will focus on analytically modeling the vehicle interactions in mixed traffic with faster non-stopping vehicles and vehicles frequently stopping similar to the approach for cars and buses by Loder *et al.* (2019b).

This research studies how the rise of (pooled) automated taxis will impact performance of urban road networks. To do so, it uses a static[5] trip-based simulation tool based on the macroscopic fundamental diagram to study possible future scenarios. To the authors' best knowledge, this is the first attempt to apply the MFD for prediction of future traffic states. Although the assumptions for both the model and the future scenarios are based on earlier research, the approach relies on various simplifications, which should be addressed once better information becomes available. This concerns not only capacity impacts of vehicle-automation, but in particular travel demand patterns, which may be substantially different in the future (Meyer *et al.*, 2017). This also includes potential empty travel, which was neglected in this approach. Methodologically, the key limitation is the decoupling of modes. It is hard to imagine entirely separate infrastructures for the different kinds of automated taxis. As a result, the effective network speeds will likely be lower than indicated by the results of this paper. Also the solution of the bathtub model used in this research is not precise (Arnott and Buli, 2018; Mariotte *et al.*, 2017; Aghamohammadi and Laval, 2018), but only approximated. However, this is not assumed to substantially bias the results.

Despite above limitations, this first analysis already provides relevant insights: First, it is shown that assuming only current demand for car-travel, vehicle automation may indeed

[5] As described above, speeds are constant within a trip.

allow substantial increases in network performance (as suggested earlier (Tientrakool *et al.*, 2011; Friedrich, 2016)). The positive impacts scale with the possible capacity gains through automation and may be further increased by an uptake of pooled automated taxis.

However, vehicle automation may not only increase road capacity, but also reduce taxi fares to a level comparable with public transportation. Moreover, it may allow a more efficient use of in-vehicle time. Both effects make car travel (individual or pooled) more attractive and are hence likely to attract current public transport users (Bösch *et al.*, 2018). For the analysis, the extreme case of all current bus and tram users switching towards car travel was analyzed. In fact, this may even constitute a conservative estimate of future demand given that may be substantial demand increases through new user groups (e.g. children and elderly) or induced demand effects due to higher comfort levels or changed land-use patterns. The results show that in such a case, substantial capacity gains of at least 40 % (the level expected by Friedrich (2016)) will be required to maintain the current network performance. If a substantial share of automated vehicles will be operated in private possession with high shares of empty travel, even larger increases in capacity will be required.

On a second note, the results show that a large share of pooled taxi trips is required to achieve a system-optimal state. Yet, it is expected that pooled rides will not be substantially cheaper than individual rides (Bösch *et al.*, 2018). Moreover, higher privacy and comfort will likely outweigh the small differences in fares. Moreover, realized capacity benefits may likely be lower in case mixed traffic of automated and non-automated vehicles was allowed in the network.

9 Conclusion

The results of this research show that vehicle automation will impact cities differently. The first case of "only current car demand" can be thought to apply to car-oriented North American cities, e.g. Los Angeles, CA. In such cases, vehicle-automation will likely bring substantial benefits in network performance. Moreover, cheaper taxi travel may in the long-run even reduce space requirements for parking.

The second case (current car + bus/tram demand) applies to transit-oriented cities like Zurich, Switzerland. In those cities, replacing existing public transport will likely decrease productivity of networks, and thus accessibility, with substantial economical ramifications (Venables, 2007). Yet, given the low expected cost of automated taxi services and the small fare difference between individual and pooled taxis (Bösch *et al.*, 2018), strong policy measures will have to be developed to maintain a high level of public transport use. Without such measures, only capacity gains of 40 % or more will allow to maintain the current level of network performance. However, although such high capacity increases were predicted by early research (Friedrich, 2016), later studies expect the true impacts to be much smaller (Le Vine *et al.*, 2015). In reality, required capacity gains may even be higher due to induced demand and new user groups.

10 Acknowledgements

This work was supported by ETH Research Grant ETH-04 15-1.

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