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Effects of driverless vehicles – Comparing simulations to get a broader picture

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Driverless vehicles have the potential to significantly affect the transport system, society, and environment. However, there are still many unanswered questions regarding what the development will look like, and there are several contradictory forces. This paper addresses the effects of driverless vehicles by combining the results from 26 simulation studies. Each simulation study focuses on a particular case, e.g. a certain mobility concept or geographical region. By combining and analysing the results from the 26 simulation studies, an overall picture of the effects of driverless vehicles is presented. In the paper, the following perspectives are considered: what types of application of driverless vehicles have been studied in literature; what effects these simulation studies predict; and what research gaps still exist related to the effects of driverless vehicles. The analysis shows that it is primarily driverless taxi applications in urban areas that have been studied. Some parameters, such as trip cost and waiting time, show small variations between the simulation studies. Other parameters, such as vehicle kilometres travelled (VKT), show larger variations and depend heavily on the assumptions concerning value of time and level of sharing. To increase the understanding of system level effects of driverless vehicles, simulations of more complex applications and aspects such as land use, congestion and energy consumption are considered.

Keywords: *automated vehicle, autonomous taxi, driverless vehicle, societal effects, traffic simulation*

1. Introduction

The development of automated driving technology and its use in driverless automated vehicles is moving fast, and the technology has the potential to significantly affect the transport system, society, and the environment. However, there are still many unanswered questions regarding what this development will look like and several opposing forces exist (Milakis et al., 2017; Pernestål Brenden et al., 2017; Townsend, 2014). For example, automation may lead to increased road capacity, which has the potential to reduce congestion. On the other hand, the opportunity to use the time in the car for things other than driving, lower marginal travel costs, and new user groups may lead to increased traffic (Litman, 2015). There is still a lack of understanding of what the overall effect will be in these situations as the comprising effects point in different directions. Furthermore, the

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societal effects of driverless vehicles do not come directly from the technology itself, but rather from how it is used (Barth et al., 2014; Brown et al., 2014; MacKenzie et al., 2014).

To obtain quantitative estimations of system effects, simulation models can be used. For simplicity, simulation models in this paper are used in their broadest sense and encompass both analytic and simulation-based transport models. Using simulation models, the effects of specific variables, such as trip cost, fleet size, and travel demand, can be investigated. Operational simulation models have become more and more sophisticated during the latest decades, and heterogeneous individuals and complex interactions can now be simulated, for example by using agent-based models (Bonabeau, 2002; Duncan, 2010). However, setting up such simulation models is a complex task, and typically a large amount of data, time, and effort is needed to calibrate these models. The data can be challenging to collect, in particular data on the effects of automation as such systems do not exist yet. Therefore, researchers must rely on thin data and many assumptions. Also, for many simulation models, run time is dependent on the size of the network and the complex interactions between some variables, and therefore assumptions, such as fixed travel demand, are often made to reduce run time and the complexity of the simulation. The models are thus built for specific areas and are in general used for case studies. Therefore, the results from a single simulation model may be difficult to generalise.

In the literature there are a number of simulations studying different aspects of effects of driverless vehicles. Each of these simulation studies can be seen as a case study. By reviewing the simulation studies, comparing them, and acknowledging that they describe different cases with different assumptions, this paper contributes to providing a broader picture of the effects of driverless vehicles. By using this approach, the paper addresses questions such as: which type of application areas and mobility concepts are covered in the existing simulation literature?; what are the effects on performance indicators such as trip cost, vehicle kilometres travelled (VKT), fleet size, waiting time etc.?; and what are the existing research gaps?

The paper continues in the next section by describing the methodology. Section 3 then gives an overview of the reviewed simulation studies. In Section 4, analysis is performed regarding type of applications studied and comparison of effects of driverless vehicles. Section 5 discusses areas for future work, and Section 6 concludes.

2. Methodology

The method used in this paper is to set up clear search strategies and selection criteria for which simulation studies to include, and to review, compare and analyse these studies with an aim to add value beyond an overview (Wee and Banister, 2016). Database searches in combination with forward and backward snowballing (Jalali and Wohlin, 2012) have been used to identify relevant peer-reviewed papers that present simulation studies of driverless vehicles. The keywords "autonomous vehicle(s)" and "driverless vehicle(s)" combined with "impact AND service", "taxi", "fleet size" and "model" in title, abstract and keywords were used as search terms in Scopus (www.scopus.com) and Google Scholar (scholar.google.com). This initial search resulted in a set of 21 papers considered relevant for the scope of this literature review. With these papers as a base, another five relevant papers were found via backward and forward snowballing. Thus, the literature search resulted in 26 papers reviewed and included in the analysis. It should be noted that in many of the reviewed papers several simulation scenarios have been performed, typically on different mobility concepts.

A number of criteria were applied in selection of relevant papers. First, this review is limited to passenger transport. Second, it considers only conditionally or fully driverless vehicles, i.e. driverless vehicles of SAE level 4 operating only in its operational design domain, or driverless vehicles of SAE level 5 (SAE International, 2016). Third, papers have only been selected if they conduct numerical simulations of travel demand or traffic flow. Fourth, only papers that present results on a *network level* have been selected. There are a number of papers, see e.g. (van den Berg and Verhoef, 2016; Ye and Yamamoto, 2018), that study the effects of driverless vehicles on traffic flow and capacity on a road segment (e.g. a motorway link), but these are excluded from this review. Fifth, only papers that explicitly assume driverless vehicles are included in the comparison. There is a related research field studying large-scale on-demand mobility and large-scale car/ride sharing, see e.g. (Alonso-Mora et al., 2017; Fiedler et al., 2017). Although related to this study, those studies do not include the specific features of driverless vehicles, including e.g. the change operational cost that is expected when the driver is removed.

Also within the chosen set of papers, there are limitations in the review. Even though some of the chosen papers evaluate different dispatch strategies, there is no intention to try to compare the effects of these. Rather, focus of this review is on system effects such as vehicle kilometres travelled, fleet size, and waiting time.

To make an overview of the reviewed papers, nine dimensions are selected: simulation approach; scale of application; mobility concept; penetration rate; travel demand; trip cost; vehicle kilometres travelled; fleet size; and waiting time. The first five dimensions are chosen to compare the set-up of the simulation studies. The other dimensions are chosen to compare reported effects of driverless vehicles. The result dimensions are chosen by identifying which are the main variables for which results are reported in the reviewed papers. Most of the nine dimensions can either constitute assumptions and be given as input to the simulation models or be a result from the simulation. The nine dimensions are further described in Section 3.1.

The comparison goes beyond these nine dimensions, and other aspects such as geographical and behavioural aspects are also discussed. In the paper, analysis and synthesis have been used to extract new knowledge from the full set of reviewed papers, in order to move a step further rather than solely discussing results of individual papers.

3. The reviewed simulation papers

An overview of the papers included in the analysis is presented in this section. Out of the nine dimensions chosen for the overview, the first five (simulation approach, scale of application, mobility concept, penetration rate, and travel demand) describe the simulation study, i.e. the model set-up for the case studied. The remaining four dimensions (trip cost, vehicle kilometres travelled, fleet size, and waiting time) represent effects of driverless vehicles. These particular dimensions were chosen to represent the effects because they are the four most frequently reported simulation result dimensions in the reviewed papers. There are also other dimensions, e.g. parking demand, mode choice, and energy consumption that are relevant, but they were left outside the overview table as they are only discussed in a smaller number of the reviewed papers. However, they are included in the analysis of this paper. In Section 3.1, the meaning and scope of each column in the overview table is described in more detail.

3.1 Dimensions for comparison

Different **simulation approaches** are used in the reviewed papers in order to study the effects of driverless vehicles. The classification of simulation approach in this paper follows the level of detail classification by Hoogendorn and Bovy (2001), who categorise transport models in five dimensions: scale of the independent variables (continuous, discrete, semi-discrete); level of detail (sub-microscopic, microscopic, mesoscopic, macroscopic);

representation of the processes (deterministic, stochastic); operationalisation (analytical, simulation); and scale of application (networks, stretches, links, and intersections). The level of detail of the simulation approaches in the reviewed papers ranges from sub-microscopic, via microscopic and mesoscopic, to macroscopic. Note that sub-microscopic simulation is sometimes also called agent-based simulation or nano-simulation (Duncan, 2010). The term agent-based simulation will be used in this paper rather than sub-microscopic, since it more clearly describes the modelling strategy taken. Agent-based models are at the highest level of detail and simulate travellers as they choose mode and route in the network. On a slightly coarser level, microscopic models simulate individual vehicles and their routes in the network, assuming a fixed mode choice. Macroscopic models on the other hand, simulate flows of vehicles and how link travel times vary with link flow.

The **scale of application** describes the size of the area studied in the simulation. Comparing to the scale of application classification by Hoogendorn and Bovy (2001), only networks and stretches are relevant for this paper. Therefore, networks are further classified into city centre networks, small city networks, large city networks, region/state networks, and country networks. If information exists, the scale of application is also described by the size of the studied area in square kilometres, number of inhabitants in the studied area, and time-period for the simulation.

Mobility concept refers to the type of operation the driverless vehicles are used for. The nomenclature for mobility concept is not consistent in literature. In particular, terms such as “automated”, “autonomous”, “self-driving”, and “driverless” vehicles are used variously in the literature. To stress that this review focuses on vehicles without a driver, i.e. SAE levels 4 and 5, the term “driverless” is chosen in this paper. To be able to compare mobility concepts across reviewed papers, the definition presented in Table 1 is used throughout this paper. The need to distinguish in this paper between shared vehicles and shared rides led to the choice of using the terms “driverless taxi” and “shared driverless taxi”, which in previous literature are both often called “shared autonomous vehicles”. This means that the nomenclature used in this paper may deviate from the nomenclature in the original papers. However, the interpretation of the service is the same.

Table 1. Nomenclature for mobility concepts.

Abbreviation	Description
CDC	Conventionally Driven Car. Privately owned, manually driven.
PDV	Privately owned Driverless Vehicle. Can be shared within the family.
DT	Driverless Taxi (up to six passengers). Vehicles are operated as a fleet. Shared vehicles, but not shared rides.
SDT	Shared Driverless Taxi (up to six passengers). Vehicles are operated as a fleet. Shared vehicles and shared rides.
SBDT/SBSDT	Station Based DT/SDT. DT or SDT that operates between stations or defined pick-up points, i.e. the travellers must walk to the stations to start their ride.
DB	Driverless Bus (> six passengers). Shared vehicles and shared rides.

Penetration rate refers to the share of trips in the simulation study that are performed with driverless vehicles using any of the mobility concepts described above. In one case (W. Zhang et al., 2015), penetration rate refers to the share of agents using driverless cars rather than the share of trips. The type of trips replaced by driverless cars differs in the papers and is therefore also stated in the penetration rate column, e.g. per cent of private car trips/public transport trips/taxi trips/all trips.

Travel demand is the number of person trips included in the simulation study. It can be given as input data and assumed to be fixed, or it can be modelled using choice models and thus an output. The travel demand also provides an indication of the size and the length of the scenario modelled.

Trip cost is here the marginal monetary cost of driving for car trips, i.e. not including the cost of buying the car. For public transport, trip cost is the same as ticket price. In Table 2, trip cost has been translated to Euro by using the exchange rate of $1 = € 0.845.

Vehicle kilometres travelled (VKT) is the total sum of all kilometres travelled by vehicles during the simulation time, including both empty and occupied kilometres. In Table 2, VKT is presented as a change in percent. As the base line scenario varies between the papers (some use e.g. VKT by CDC as a base line, while others use a certain mobility concept), a brief description of the reasons for the change is also provided. The reasons for VKT changes in the reviewed papers are: that driverless vehicles drive without passengers to pick up the next passenger or to go to a parking place (called "empty kilometres" in Table 2); that they drive empty to relocate in a speculative manner to reduce waiting time for potential future passengers (called "relocation" in Table 2); and due to changes in ride sharing schemes, mode shares and trip generation.

Fleet size is either expressed as the number of vehicles used in the service, or as the number of CDC or conventional buses one automated vehicle replaces. Explicit numbers of the fleet size provide an indication of the size of the application to be modelled.

Waiting time is an output from most of the simulation studies and indicates service level. It is given in minutes or as a percentage of current bus or car travel time.

3.2 Overview of the simulation studies

In Table 2, papers are arranged by the size of the areas studied, ranging from a single line to a whole country. As the different simulations have different intentions, the parameters, inputs and outputs used vary. In Table 2, regular style indicates assumptions used in the simulations, including values that were given as input or used as parameters in the simulation. Italic style indicates simulation outputs. If several mobility concepts are studied in one paper, they are marked with (a), (b) etc. In most papers, simulations are performed with several different parameter settings. However, as Table 2 is only an overview, the aim here has been to identify the main results of each paper rather than presenting all results. Specific results and perspectives that are not covered in the overview table are further discussed in Section 4.3. In Table 2, percentage values have been rounded to the nearest integer, and time values to the nearest tenth of a minute.

Table 2. Overview of the reviewed simulation studies.

#	Author	Simulation approach	Scale of application	Mobility concept	Penetration rate	Travel demand	Trip cost	Vehicle kilometres travelled	Fleet size	Waiting time
1	Winter et. al (2016)	Microscopic	Stretch Predefined line 7 km in the Netherlands 1 day	DB (10 passengers)	100% of all trips for the given road stretch	3,693 trips for 1 day	*1.95 €/pass. = 0.23 €/km*	-	*N = 224*	*2.2 min*
2	Dia and Javanshour (2017)	Agent-based	City centre network 6 km² Melbourne Trips within the area 07:00-09:00	(a) PDV (25%) + DT (75%) (b) DT	100% of private car trips within the area	(a) 2,136 trips (b) 2,059 trips for 2h	-	*(a) +29% (b) +10% due to empty km and relocation*	*(a) N = 1217, 1 PDV = 1.75 CDC (b) N = 247, 1 DT = 8.3 CDC*	(a) 0 min *(b)1.0 min*
3	Azevedo et. al (2016)	Agent-based	City centre network 14 km² Singapore Trips within the area 03:00-15:00	SDT	100% of all trips. No private cars allowed within the area	40,080 trips for 12h	40% of CDC taxi	-	*N = 2400*	*5 min*
4	Marczuk et. al (2016)	Agent-based	City centre network 56 km² Singapore, trips outside truncated 03:00-24:00	DT	100% of all trips except subway trips and public buses	363,859 trips for 15h	-	-	*N = 25000-35000, 23-28% decrease due to relocation*	*10 min*
5	R. Zhang et. al (2015)	Macro-scopic	City centre network Manhattan Three time-periods 04:00-05:00 16:00-17:00 19:00-20:00	SBDT	100% of taxi trips within the area	1,982 trips (low) 16,930 trips (average) 29,485 trips (high) for 1 hour	-	-	*N = 8000 (70% of conventional taxi fleet)*	*2.5 min*

6	W. Zhang et. al (2015)	Agent-based	City centre network 10x10 miles Artificial gridded city 1 day	SDT	2% of agents, 100% of all trips of these agents	37,900 trips for 1 day	0.13 -0.21 €/km	*+15-60% due to empty km and relocation*	*N = 650-800, 1 SDT = 14 CDC*	*2.3 min (no relocation) 1.7 (relocation)*
7	Fagnant and Kockelman (2014)	Microscopic	City centre network 10x10 miles Artificial gridded city Trips < 15 miles 1 day	DT	4% of private car trips	*60,551 trips for 1 day*	-	*+5% (no relocation)* *+11% (relocation)*	*N = 1688,* *1 DT = 14 CDC*	*<20s*
8	Hörl (2017)	Agent-based	Small city network Artificial city 84,000 inhabitants Peak hours 07:00-10:00 and 16:00-18:00	(a) DT (b) SDT in competition with car, bus, walk	*(a) 46%* *(b) 37%* *of all trips*	-	(a) 0.47 €/km (b) 0.243 €/km	*(a) +28%,* *(b) +31%* *due to empty km*	(a) N = 1000 (b) N = 1000	*(a) 4.6 min* *(b) 3.8min*
9	Merlin (2017)	Agent-based	Small city network Ann Arbor 120,000 inhabitants 1 day	(a) DT (b) SDT	100% of PT trips	-	*(a) 0.51 €/km* *(b) 0.23 €/km*	*(a) 1200% of bus VKT* *(b) 500% of bus VKT*	*(a) 1 bus = 12.3 DT (N = 800),* *(b) 1 bus = 6 SDT (N = 400)*	*(a) 5.6 min* *(b) 5.9 min (bus 6.2 min)*
10	Lu et al. (2018)	Agent-based	Small city network Ann Arbor 20 000 commuters 1 day	(a) DT, SDT (b) DT, SDT in competition with private car	(a) 100% *(b) -*	-	DT 0.525 €/km	*(a) +34%* *(b)~+22%*	*(a) N = 4000* *(b) N = 2539 (+10555CDC)*	*(a) 2.7 min* *(b) 0.1-0.6 min*
11	Burghout et. al (2015)	Microscopic	Large city network Stockholm 2 million inhabitants 1 day	(a) DT (b) SDT	100% of private car trips	271,868 trips for 1 day	-	*(a) +24%* *(b) -24%* *compared to CDC, due to empty km*	*(a) 1 DT = 12 CDC* *(b) 1 SDT = 20 CDC*	*(a) 0 min* *(b) 8.4 min*

12	Bischoff and Maciejewski (2016a)	Agent-based	Large city network Artificial city based on Berlin 1 day	DT	100% of private car trips within the city	2.5 million trips for 1 day	-	*+16% due to empty km*	*N = 100000, 1 DT = 10 CDC*	*2.3 min*
13	Dandl and Bogenberger (2018)	Mesoscopic	Large City Network Munich 10 days	DT	100% of DriveNow car rental trips	-	0.25-0.27 €/km	*+10-15% due to empty km*	*N = 150-200 1DT = 2.8-3.7 rental car*	*1.9-2.4 min*
14	Fournier et al. (2017)	Agent-based	Large City network. Artificial city (892 km^2) based on Berlin 07:00-08:00	DT	100% of private car trips	240,396 trips	0.26 €/km	-	N= 130000	*0.72 min*
15	OECD International Transport Forum (2015)	Agent-based	Large city network Lisbon 1 day	(a) DT (b) SDT	(a) 50% of private car trips 100% of public transport trips (b) 100% of private car trips 100% of bus trips	-	-	*(a) +91% due to empty km, relocation, replacement of metro and buses (b) +6% due to empty km, relocation, replacement of buses*	*(a) 107% of their baseline fleet (CDC) (b) 10.4% of their baseline fleet (CDC)*	*(a) 3.3 min (b) 3.8 min*
16	Shen and Lopes (2015)	Agent-based	Large city network New York City 1 day	DT	100% of taxi trips	~340,000 trips for 1 day (2013 taxi data)	-	-	N = 12216	*6.3 min (77% of CDC taxi)*
17	Dandl et. al (2017)	Microscopic	Large city network Munich (within area) 05:00-11:00	DT	10% of private car trips	40,000 trips for 6h	-	*+10% due to empty km*	N = 4000	*~5 min*

18	Hyland and Mahmassani (2018)	Agent-based	Large city network, artificial city 1619 m² based on Chicago. 1 day	DT	50% of taxi trips	1500-3000 trips per hour	-	*+ 28-35% due to empty km (22-26% of all km included empty km)*	N = 325-400	*2.2-8 min*
19	Loeb et al. (2018)	Agent-based	Large city network based on Austin 1 day	DT	2% of all trips	~8800 trips per day	-	*+20% due to empty km and charging*	N = 5 travellers/veh	*3.9-6.3 min*
20	Gurumurthy and Kockelman (2018)	Microscopic	Large city nework Orlando	SDT	*50% of CDC trips*	~1.4 million trips/day	-	*-3% due to sharing*	N = 60000 1 SDT = 6CDC	Up to 10 min
21	Chen and Kockelman (2016)	Agent-based	Large city network 100x100 miles Artificial gridded city 1 day	DT in competition with car and PT	*14-39% of all trips*	*3.6-4.3 million trips for 1 day*	0.39-0.53 €/km	*+ 7-9% due to empty km*	*N = 84945, 45,9 trips/veh & day*	*3.1 min*
22	Chen et. al (2016)	Agent-based	Large city network 100x100 miles Artificial gridded city 1 day	DT	10% of all trips	680,000 trips for 1 day	*0.22-0.25 €/km (occupied km)*	*+ 7-14% due to empty km, charging, relocation*	*N = 29939-41179 depending on charging needs*	*7.7-9.5 min*
23	Brownell and Kornhauser (2014)	Agent-based	Region/State network New Jersey 1 day	SDT (two different sharing schemes)	100% of all trips	32 million trips for 1 day	*0.22- 0.39 €/km*	*-19% due to improved sharing scheme, compared with other SDT application*	*N = 1.61-4.45 million*	max 5-7 min
24	Childress et. al (2015)	Agent-based	Region/State network Puget Sound region Washington state 1 day	(a) PDV in competition w. walk, PT (b) DT in competition w. walk, PT	*(a) 43-45%* *(b) 29%* *of all trips*	*(a) 4.1-4.3* *(b) 4.1* *trips per person*	(a) Same as for CDC (b) *0.87 €/km*	*(a) 4-20% compared to CDC, due to parking at home, new trips* *(b) -35% compared to CDC, due to lower mode share*	-	-

25	Davidson and Spinoulas (2016)	Mesoscopic	Region/State network Southeast Queensland 1 day	(a) PDV (b) DT (c) SDT In competition with walk, public transit, CDC	(a) 62% (b) 100% (c) 100% of private car trips	(a) +15% (b) +10% (c) +15% compared to CDC trips	Operation cost 50% of CDC	*(a) +36% (b) -8% (c) -9% due to changes in travel demand.*	-	-
26	Meyer et. al (2017)	Macro-scopic	Country network Switzerland 1 day	(a) PDV (b) DT	(a) 100% of car trips (b) 100% of car trips + 100% of public transport trips	-	-	*(a) 69% due to new trips and empty km. (b) 15-195% depending on region, due to empty km and new trips*	-	*Accessibility increase: (a) +10% (b) + 1%*

4. Analysis

This section provides an analysis of the reviewed simulation papers, including the dimensions selected in Table 2, as well as other dimensions. Thus, this analysis is based on the full papers and not only on the overview presented in Table 2.

4.1 What applications are studied?

The scale of application in the reviewed simulations ranges from a 7 km road stretch in the Netherlands to the whole road network of Switzerland. The spread is also large for travel demand, which varies from a few thousands to several millions of trips. Also, the simulated time-period varies in the papers from one hour up to a full day (24 hours).

There is a substantial imbalance in existing literature regarding which applications are studied. Figure 1 illustrates the distribution of the reviewed simulation papers across the dimensions of mobility concept and scale of application. The figure shows that focus in existing literature is on larger cities or parts of larger cities (e.g. Fagnant and Kockelman (2014), Dia and Javanshour (2017), and Dandl and Bogenberger (2018)). Also, there is a focus on studies of the mobility concept DT, and to some extent SDT. One single paper simulates a driverless bus system (Winter et al., 2016), and another single paper looks into the effects for a whole country (Meyer et al., 2017).

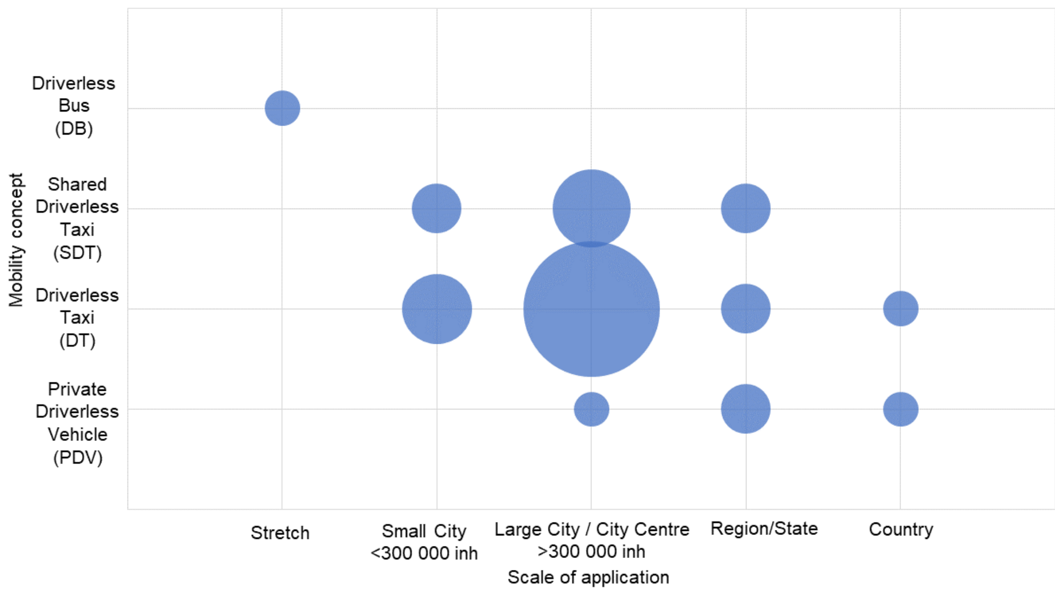

Figure 1. Distribution of the simulation studies across mobility concept and scale of application for the reviewed papers. Circle size shows number of studies for the given combination of mobility concept and scale of application.

One conceptual difference between the simulations is who is in focus in the optimisation – the individual user by minimising waiting time or the system operator by minimising fleet size and operational cost? In most studies, the system operator is at the centre of the optimisation while fulfilling maximum waiting time requirements (e.g. R. Zhang et al. (2015), Bischoff and Maciejewski (2016a), and Loeb et al. (2018)). In comparison, e.g. Winter et al. (2016) and Dandle and Bogenberger (2018) also take the users' value of travel time into account in the optimisation.

When comparing simulation approaches, it can be seen that most of the simulation studies in this review take an agent-based approach (e.g. Shen and Lopes (2015) and Hörl (2017)). One likely reason that an agent-based approach is chosen in so many of the papers is that many of the studies require simulation of agents and how they are transported in the network, allowing also for several agents to use the same driverless vehicle. Simulation of shared driverless taxis requires that trip scheduling is taken into account, i.e. allocation of empty rides and development of ride sharing schemes. This is a new modelling step which is not included in conventional transport models that typically use origin-destination matrices of trips as input, without information about the agents performing these trips or which agents share a ride.

Regarding penetration rate, most of the reviewed simulation studies assume either that all private car trips or all taxi trips within the area are replaced by driverless vehicle trips. Two exceptions are Chen et al. (2016) and Dandl et al. (2017), who assume that 10% of car trips are replaced by DT. A couple of papers include a mode choice model (e.g. Chen and Kockelman (2016) and Childress et al. (2015)), and the share of driverless vehicles is then a result of the simulation.

4.2 What are the main reported effects?

In this section, the effects of driverless vehicles from the perspectives presented in Table 2, i.e. trip cost, VKT, fleet Size, and waiting time, are analysed.

Trip cost

The reviewed papers present two major ways of calculating trip cost; one is based on vehicle related operational costs (Brownell and Kornhauser, 2014; Chen et al., 2016; Chen and Kockelman, 2016; Fournier et al., 2017; Merlin, 2017; Winter et al., 2016), while the other assumes a price estimated to be a fraction of the cost for conventionally driven cars and taxis (Azevedo et al., 2016; Childress et al., 2015; Davidson and Spinoulas, 2016; R. Zhang et al., 2015).

For DT, the estimated trip cost based on operational costs ranges from 0.25-0.53 €/km in most papers. Chen et al. (2016) and Fournier et al. (2017) estimate the cost per occupied kilometre as €0.22-0.26, but do not include the cost for empty kilometres. Childress et al. (2015) assume that the price for DT will be similar to the price for Uber, and give the higher estimate of 0.87 €/km. For SDT, the price per km ranges between €0.13-0.39, with most studies resulting in prices around €0.23. The estimated price for DB is around 0.23 €/km. In the cost calculations, the cost for the automated vehicle (a cost estimate that ranges from €59,150 to €100.000 in the reviewed papers) is considered. Also costs for maintenance, tyres and fuel/electricity are taken into account. However, Gawron (2018) showed that energy consumption for driverless vehicles may increase by up to 35% compared to CDC due to computations and data transmission, a fact that will affect both the trip cost and environmental effects. Such increases are not considered in the reviewed papers. Furthermore, the reviewed papers focus primarily on the vehicle related costs, but for DT, SDT and DB services there will also be costs related to the fleet management and the booking/ticketing systems that are not fully considered. In particular, cleaning to keep shared vehicles at a sufficiently high standard can be costly (Bösch et al., 2018).

Childress et al. (2015) discuss that transforming from car ownership to using mobility services such as DT or SDT decreases the investment cost for the user, but increases marginal costs per trip. Davidson and Spinoulas (2016) argue that modal choice is primarily based on the marginal cost per trip rather than the total costs, and show that travel demand will be reduced for DT/SDT services compared to CDC and PDV.

VKT

VKT relates to energy consumption and is thereby connected to emissions and environmental effects. It also relates to utilisation of the street space, as the streets will be more crowded if there are more vehicles driving around.

For PDV and the most common assumption that "all cars are driverless", there is an increase in VKT of 20-70% (Childress et al., 2015; Dia and Javanshour, 2017; Meyer et al., 2017), see Figure 2. The span depends primarily on the difference in assumptions regarding demand increase and on empty kilometres. Demand changes depend on assumptions about new user groups, increased capacity, and reduction in value of time (VOT), while empty kilometres depend on assumptions on where parking is performed and on sharing within the family.

Figure 2 shows a diverse picture of the VKT change for DT services. For most DT services the increase in VKT is about 5-35%, typically around 10-15%. The changes are primarily due to empty kilometres and relocation of vehicles. However, the OECD International Transport Forum (2015) report a high VKT increase of around 90%, primarily due to relocation and the fact that the DT system is assumed to replace all public transport except high capacity modes such as metro, light rail, and trains. Meyer et al. (2017) report as a maximum 195% region-specific increase in VKT due to empty trips, and generation of new trips. On the other hand, Childress et al. (2015) report a VKT decrease of about 35% as an effect of the reduced demand due to a relatively high price for the DT service compared to other modes.

For SDT, Figure 2 shows that VKT changes range from -25% to +30% compared to CDC. If all rides that, under some constraints on service level, can be shared are shared, significant decreases in VKT can be achieved for SDT in comparison with DT (Burghout et al., 2015; Merlin, 2017; OECD International Transport Forum, 2015). On the other hand, if a choice model based on trip cost and VOT is used to let agents decide on their mode, a lower percentage of shared rides is achieved (Hörl, 2017). This gives VKT in the same range as for DT. These results indicate that there is a potential to reduce VKT by using SDT, but the direct travel cost reductions due to sharing are not enough to achieve this potential. Merlin (2017) shows an increase in VKT as large buses are replaced with several smaller vehicles. Meyer et al. (2017) show an increase in VKT due to an increased demand. Zhang et al. (2015) report a VKT increase of up to 60% due to a relocation strategy that allows for extensive cruising in order to reduce parking demand. There are no VKT changes reported for the DB study and therefore this category is not included in Figure 2.

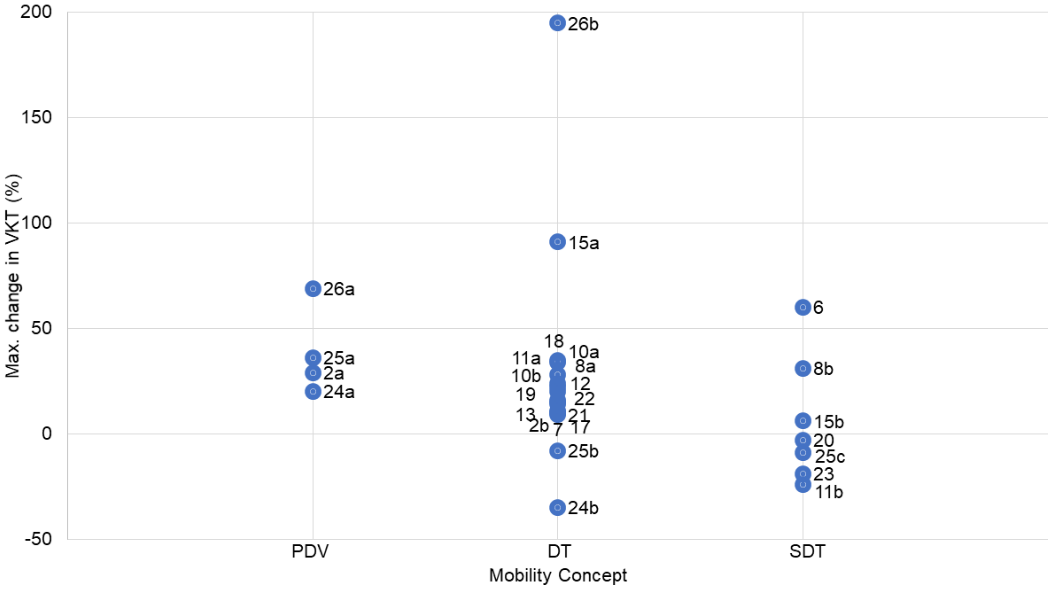

Figure 2. The relation between changes in VKT and mobility concept in the simulation studies.

Penetration rate has a significant impact on VKT for SDT (OECD International Transport Forum, 2015). On the other hand, penetration rate has smaller impact on VKT for DT. This suggests that SDT needs a higher travel demand, which in turn mean more trips that overlap in time and distance to be effective.

One effect of increased VKT is congestion or reduced traffic flow. In most papers, this effect is not considered, while some papers handle it by reducing network speed (Fagnant and Kockelman, 2014; W. Zhang et al., 2015). Bischoff and Maciejwski (2016a) argue that the increase in VKT is met by improved traffic flow and reduced search for parking, while Meyer et al. (2017) show that for the DT application, congestion may increase significantly in downtown regions, despite assumptions about increased capacity. Dandle et al. (2017) show that if 10% of the private car trips in Munich are replaced by DT, this would lead to a 10% increase in VKT, which causes a delay for private vehicles of about 1%. However, it should be noted that travel time delay is a non-linear function of traffic volume and that it thus makes a large difference if VKT is increased in a network with traffic volumes already close to the capacity limit (May, 1990).

VKT is not evenly distributed in space or time. Empty kilometres will be less than average in city centres and significantly above average in the suburbs (Bischoff and Maciejewski, 2016b). Furthermore, VKT increases during peak hours is around double the average VKT increase (Bischoff and Maciejewski, 2016a). These effects might cause congestion in new areas in the city outskirts. It will also add more traffic during the already congested peak hours.

The driverless technology is also expected to reduce congestion by increasing road capacity, primarily on freeways. Assuming a 30% capacity increase on freeways due to the driverless technology in the PDV mobility concept, results in accessibility increases of 10-17% (Childress et al., 2015; Meyer et al., 2017).

Fleet size

Fleet size ranges from a few hundred to several million vehicles in the reviewed papers. When replacing conventional cars (CDC) with (shared) driverless taxi services ((S)DT) the required fleet size reduces substantially. Most papers present results in the order of 1 DT/SDT = 6-14 CDC. One exception is Burghout et al. (2015) who show that 1 SDT can replace 20 CDC. The main reason for this is the high level of sharing provided by waiting times and additional travel times that are longer than in the other papers. Different types of relocation strategies have an impact on fleet size, and Marczuk et al. (2016) show that predictive relocation can decrease the fleet size by 23-28%.

Figure 3 shows the relation between fleet size, as measured by number of vehicles needed to serve 1000 trips[3], and mobility concept for the simulation studies that reported values on both parameters. From the figure, one can see that fleet size is, as expected, small for shared driverless taxis (SDT) (21-60 vehicles/1000 trips) and driverless buses (DB) (61 vehicles/1000 trips). For DT, the picture is more diverse, with fleet size ranging from 22 up to 271 vehicles/1000 trips. The diverse picture for DT is due to differences in allowed maximum waiting times, relocation strategies, and whether or not the simulation accounts for relocation time of the vehicles.

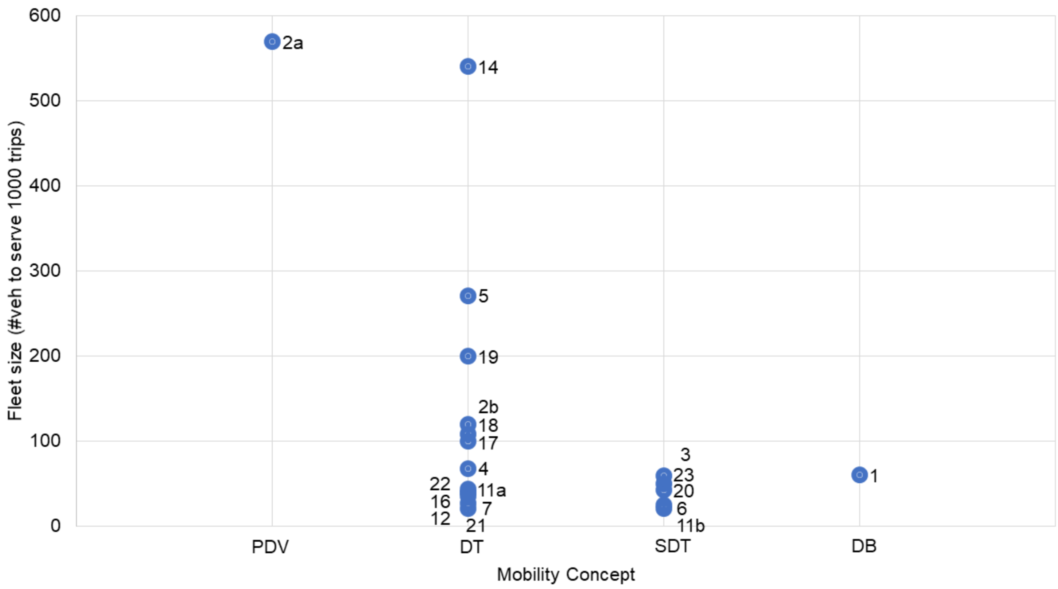

Figure 3. The relation between fleet size and mobility concept in the simulation studies.

Merlin (2017) investigates the scenario when DT/SDT services replace public transport buses. In this case 1 bus = 12 DT/6 SDT, while at the same time VKT also increases by the same order of magnitude, and the traveller waiting time decreases by around 30%. These results indicate that if the energy consumption of a DT or SDT is around 1/12 or 1/6 respectively, it may be a sustainable choice to replace public transport buses with DT/SDT systems.

Waiting time

Most of the reviewed papers use an upper bound on the waiting time to adjust the fleet size. The waiting times range from 0-10 minutes, with most simulations at around 3-6 minutes. In some applications, if trips cannot be served within maximum waiting time, the trips are left unserved (Chen et al., 2016; Dandl and Bogenberger, 2018; Loeb et al., 2018; R.

[3] It should be noted that the simulated time-period differs in the studies. Most studies simulate one day, but in some studies shorter time periods are simulated, in which case peak hour demand has been chosen to calculate fleet size. Thus, fleet size should in this paper be interpreted as a lower bound on the number of vehicles needed to serve 1000 trips.

Zhang et al., 2015). If the DT/SDT service is expected to replace privately owned cars, this is not a realistic assumption, and it would lead to reduced trust in the service.

Figure 4 shows the distribution of the simulation studies on the dimensions fleet size and maximum waiting time. Fleet size is, as above, calculated as number of vehicles needed to serve 1000 trips. Only studies that report values on fleet size, number of trips, and waiting time are included in the figure. One would expect waiting time to decrease as fleet size increases. To some extent this pattern can be seen in the figure. Studies with waiting times of more than 8 minutes have a fleet with less than 70 vehicles/1000 trips. Also, the study with a very large vehicle fleet (570 vehicles/1000 trips) is a PDV scenario with zero waiting time. There are, however, a number of studies (in the lower left corner of Figure 4) that show relatively short waiting times despite a small vehicle fleet. Explanations found in the studies are that the waiting time/fleet size ratio is also dependent on the area served (Hyland and Mahmassani, 2018) and the charging needs of electric vehicles (Loeb et al., 2018). Furthermore, the definitions of waiting time differ between the studies.

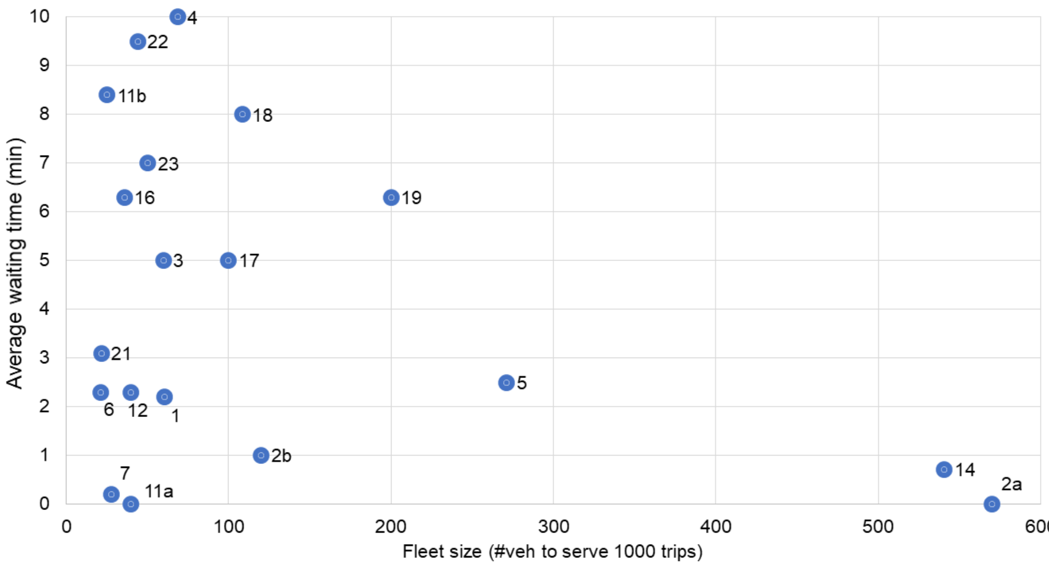

Figure 4. *Distribution of the simulation studies on waiting time and fleet size.*

Also, mobility concept and penetration rate has an impact on waiting time, in particular for SDT services (OECD International Transport Forum, 2015). W. Zhang et al. (2015) show that relocation of empty vehicles, where vehicles move in a speculative manner to come closer to potential customers, can have a positive impact on waiting time. On the other hand, relocation increases VKT.

4.3 Which other effects are discussed?

There are also several effects of driverless vehicles that are discussed in only a smaller subset of the reviewed papers. These are analysed in this section.

Land use

Parking demand can, as a consequence of reduced numbers of vehicles in the DT and SDT services, be reduced by around 83-94% (Dia and Javanshour, 2017; Fournier et al., 2017; OECD International Transport Forum, 2015; W. Zhang et al., 2015). However, OECD International Transport Forum (2015) shows that penetration rate is important for parking demand. For 50% penetration of driverless vehicles, the parking demand ranges from 76-104% of the 2015 needs (depending on the presence of public transport), while for 100%

penetration the parking demand is about 6-16% of the 2015 needs. These differences primarily depend on the fact that for a lower penetration rate there will be a larger total fleet size due to the co-existence of conventional cars and DT vehicles. Parking demand is not dependent on the willingness to share rides, and is higher in areas that attract trips, e.g. in city centres (W. Zhang et al., 2015). Dia and Javanshour (2017) show that if CDCs are replaced with PDVs that return back to home for parking, the area required for parking can be reduced by 58%. However, this comes with the cost of increased VKT. The land use needed for **stations and hubs**, including parking for idle vehicles and pick-up/drop-off zones, is only briefly touched upon in some of the papers, and there are in general no reports on the number of vehicles that are located at the same station or parking at the same time.

Geographical differences

Bischoff and Maciejewski (2016b) show that both waiting time and empty kilometres will be larger in the suburbs than in the city centre, a factor that could lead to increased urbanisation and movement to city centres. Contrary, the simulations by Meyer et al. (2017) show that accessibility is expected to decrease by up to 29% in city centres, while it increases by more than 28% in some "well connected suburbs" both for PDV and DT, results that may lead to increased attraction to suburbs and thereby increased urban sprawl. The main difference between the papers is that Meyer et al. (2017) take an increased travel demand into account, while Bischoff and Maciejewski (2016b) use today's demand. In general, there is a tendency that increases in traffic, parking demand, and congestion are enhanced in city centres (Bischoff and Maciejewski, 2016b; Meyer et al., 2017; W. Zhang et al., 2015).

Energy consumption

Three papers (Fournier et al., 2017; Lu et al., 2018; Merlin, 2017) consider CO2/green-house gas emissions, showing that emissions may increase or decrease. It should be noted that these comparisons are very sensitive to the assumptions made about the vehicle fleet (Gawron et al., 2018; Greenblatt and Saxena, 2015).

Travel behaviour

W. Zhang et al. (2015) and Hörl (2017) show that if travellers are given the choice to share a ride or not, only a small number of the trips are shared. Based on the fraction of overlapping rides, i.e. rides that can be shared, a higher level of sharing is expected. The reason for the small number of shared rides is that VOT is higher for shared rides combined with increases in travel time and travel time uncertainty. This leads to a resulting generalised time cost for the traveller, which in most cases is not compensated for by the reduced travel cost. Under plausible variation of VOT (50-110% of private car VOT) and travel cost, the share of DT (in competition with walk and public transport) varies between 14-39%. DT takes mode shares from CDC primarily due to changes in VOT and from public transit primarily by competing with price (Chen and Kockelman, 2016). With low VOT for, and easy access to, PDV, mode shares are primarily taken from walk (Childress et al., 2015). Winter et al. (2016) optimise the fleet size, taking both VOT and operational cost into account, which results in many vehicles and short waiting times.

4.4 Assumptions made in the studies

Simulation studies are heavily dependent on assumptions made, both in the modelling and in the input parameters. At the same time, as driverless vehicles are not yet operating at the streets and services based on them are not yet available, it is challenging to make such assumptions and select values for input parameters. This becomes clear in Figures 2-4, where the variety is large. In Sections 3 and 4, several of these assumptions are discussed.

Some assumptions, such as those presented in Table 2 (e.g. penetration rate and trip costs) are more direct. Others, such as handling of congestion or how long waiting times are handled, requires more investigations. A further investigation of assumptions made would be an interesting topic for future work.

5. Suggested future research

The reviewed papers give a good first estimate of the likely effects of driverless vehicles, especially regarding effects on trip cost, VKT, fleet size and waiting time, but also to some extent of the effects on land use, geographical differences, and travel behaviour. This section identifies important areas for future simulation studies.

One factor that will have an impact on the attractiveness of the mobility concept for driverless vehicles is the travellers' experiences at pick-up and drop-off stations, in particular for DT and SDT based services. However, these stations are generally not investigated in the reviewed papers. Important aspects to study include, but are not limited to: spatial studies/urban form (is there space for the stations within the city?); passenger experience (how many vehicles will there be at each station? If there are more than around 10 vehicles it may be difficult for passengers to find the right vehicle, a fact that could decrease the service level); and traffic flow (if pick-up and drop-off is assumed to be on the streets, how will that affect the traffic flow?).

Another important area for future research is driverless vehicles as a complement to public transport. Driverless vehicles in the form of a feeder service to public transport is a mobility concept that has been identified in the literature as relevant and promising from a sustainability perspective (Alessandrini et al., 2015; Pernestål Brenden and Kottenhof, 2018), and has been tested in the first pilots on public streets in Europe (Alessandrini et al., 2014). The OECD International Transport Forum (2015) show in their simulations that the concept of utilising high capacity public transport together with DT/SDT services is promising from a sustainability perspective. To further investigate this concept would be interesting for future research. This research would benefit from also including multi-modal trips.

Most of the simulation studies cover larger urban areas or city centres. However, VKT by car is to a large extent undertaken between cities, within smaller cities, in rural areas, and from rural areas into city centres. It would be interesting to study more applications in these areas, especially as there is a tendency for region enlargement, and since the complexity of the traffic environment in city centres with pedestrians and cyclists may lead to earlier introduction of driverless vehicles in rural areas and on highways connecting cities.

This review shows that understanding the impact that driverless vehicles will have on travel demand is a key to understanding the effects of driverless vehicles on VKT and congestion. Meyer et al. (2017) show that the expected increases in travel demand may very well offset the expected capacity increases. There are at least three reasons to believe that driverless vehicles will increase demand for travel. First, as time spent in the car can be used to perform tasks other than driving, travellers are likely to travel more. Second, travellers might relocate to live in places that require longer travel distances. Third, new user groups previously not allowed to drive may use the new services. Some research on travel demand has been presented. Truong et al. (2017) estimate increased demand for new types of services due to new user groups (elderly and young people). Krueger, Rashidi and Rose (2016) show in a stated preference survey that the adoption rate may be different in different user groups. Modelling travel behaviour is, however, difficult at this stage, since driverless vehicle mobility concepts do not yet exist as a mode choice for the travellers, and data is therefore lacking. One way of addressing this is through stated preference surveys, as e.g. in Yap et al. (2016), and combine the survey results with simulation models. Another way to tackle the lack of data is to use sensitivity analysis to study how the simulation outputs are affected by increased travel demand. Sensitivity analyses regarding demand were not performed in most of the reviewed papers. In addition to lack of data, a challenge in these types of simulation studies is the baseline for comparison. Should the baseline be today's transport system or a do-nothing scenario for the future?

The reviewed papers show that VKT will increase, except for some cases of high shares of SDT services. This is an effect that is further enhanced by the expected increase in travel demand. As touched upon in some of the reviewed papers, this will probably affect traffic flow and congestion. Traffic flow and congestion are central parameters for travel time and level of service, but also for urban planning and for policy-makers. Therefore, more detailed investigations of these effects would be interesting.

Some of the reviewed papers simulate the competition between DT and SDT services (Hörl, 2017), and between DT/SDT services and public transport (Chen and Kockelman, 2016; Childress et al., 2015; Davidson and Spinoulas, 2016; Hörl, 2017). However, none of the reviewed papers simulates more than one operator for the same mobility concept. This corresponds to the situation where there is only one operator that has a monopoly. But what happens if there are several operators and thus competing fleets of driverless taxis? Moreover, further studies of the relation between (S)DT fleets and public transport would be relevant. Also, the service offering in the simulations is assumed to be similar in the whole area, and trips crossing the boundaries of the simulation area are excluded or truncated. This calls for research on more complex mobility concepts and service offerings.

6. Conclusions

Twenty-six peer-reviewed papers that present simulation studies have been reviewed and analysed to provide a broad view of the effects of driverless vehicles. The analysis provides a broad picture of the effects that can be expected from driverless vehicles. It also identifies areas for future work and simulations that are needed to obtain a comprehensive understanding of the effects of driverless vehicles in this growing field of research.

In the reviewed simulation papers, the scale of application ranges from a single bus line to a whole country, but with a clear focus on larger cities and city centres. The reviewed papers cover five different mobility concepts, including private driverless vehicles, driverless taxi services, and driverless bus services, with most studies focusing on driverless taxi services. Penetration rates range from 2% to 100%.

There are four aspects of effects of driverless vehicles that were considered in the majority of the reviewed simulation studies: trip cost, vehicle kilometres travelled, fleet size, and waiting time. Among these, trip cost (DT: 0.5 €/km, SDT: 0.25 €/km), fleet size (1 DT = 12 CDC, 1 SDT = 16 CDC), and waiting time (~5 minutes) show only small variations across the studies. Vehicle kilometres travelled, on the other hand, shows large variations between the simulation studies (e.g. -34% to +195% for DT). VKT is to a large extent dependent on the assumptions made, e.g. trip cost and VOT. At the same time, parameters such as trip cost and VOT are uncertain, due to the limited experience of real applications.

The effects of driverless vehicles are unevenly distributed from a spatial perspective. Results indicate the in the city centres there will be more vehicles, more parking demand, shorter waiting times for DT services, and more traffic than in the suburbs. This also leads to more congestion and decreased accessibility to the city centres, while congestion will decrease on highways.

Furthermore, this review of simulation studies shows that ride sharing (in SDT services) has the potential to reduce VKT, and thereby energy consumption and congestion, if the level of sharing is sufficiently high. However, a lower trip cost due to sharing does not seem to be sufficient to attract travellers to ride sharing. To achieve sufficient levels of ride sharing that lead to VKT reductions, other incentives or policy regulations are needed.

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References

Alessandrini, A., Campagna, A., Delle Site, P., Filippi, F., Persia, L., 2015. Automated vehicles and the rethinking of mobility and cities. Transp. Res. Procedia 5, 145–160.

Alessandrini, A., Cattivera, A., Holguin, C., Stam, D., 2014. CityMobil2: Challenges and Opportunities of Fully Automated Mobility, in: Road Vehicle Automation, Lecture Notes in Mobility.

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proc. Natl. Acad. Sci. 114, 462. https://doi.org/10.1073/pnas.1611675114

Azevedo, C.L., Marczuk, K., Raveau, S., Soh, H., Adnan, M., Basak, K., Loganathan, H., Deshmunkh, N., Lee, D.-H., Frazzoli, E., Ben-Akiva, M., 2016. Microsimulation of demand and suppy of autonomous mobility on demand. Transp. Res. Rec. J. Transp. Res. Board 2564, 21–30.

Barth, M., Boriboonsomsin, K., Wu, G., 2014. Vehicle Automation and Its Potential Impacts on Energy and Emissions, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation. Springer International Publishing, Cham, pp. 103–112. https://doi.org/10.1007/978-3-319-05990-7_10

Bischoff, J., Maciejewski, M., 2016a. Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. Procedia Comput. Sci. 83, 237–244. https://doi.org/10.1016/j.procs.2016.04.121

Bischoff, J., Maciejewski, M., 2016b. Autonomous Taxicabs in Berlin – A Spatiotemporal Analysis of Service Performance. Transp. Res. Procedia 19, 176–186. https://doi.org/10.1016/j.trpro.2016.12.078

Bonabeau, E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. Proc. Natl. Acad. Sci. 99, 7280–7287.

Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transp. Policy 64, 76–91. https://doi.org/10.1016/j.tranpol.2017.09.005

Brown, A., Gonder, J., Repac, B., 2014. An Analysis of Possible Energy Impacts of Automated Vehicle, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation. Springer International Publishing, Cham, pp. 137–153. https://doi.org/10.1007/978-3-319-05990-7_13

Brownell, C., Kornhauser, A.L., 2014. A Driverless Alternative: Fleet Size and Cost Requirements for a Statewide Autonomous Taxi Network in New Jersey. Transp. Res. Rec. J. Transp. Res. Board 2416, 73–81.

Burghout, W., Rigole, P.J., Andreasson, I., 2015. Impacts of shared autonomous taxis in a metropolitan area, in: Proceedings of the 94th Annual Meeting of the Transportation Research Board.

Chen, T.D., Kockelman, K.M., 2016. Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes. Transp. Res. Rec. J. Transp. Res. Board 37–46.

Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. Transp. Res. Part Policy Pract. 94, 243–254. https://doi.org/10.1016/j.tra.2016.08.020

Childress, S., Nichols, B., Charlton, B., Coe, S., 2015. Using an Activity-Based Model to Explore the Potential Impacts of Automated Vehicles. Transp. Res. Rec. J. Transp. Res. Board 2493, 99–106. https://doi.org/10.3141/2493-11

Dandl, F., Bogenberger, K., 2018. Comparing Future Autonomous Electric Taxis With an Existing Free-Floating Carsharing System. IEEE Trans. Intell. Transp. Syst. 1–11. https://doi.org/10.1109/TITS.2018.2857208

Dandl, F., Bracher, B., Bogenberger, K., 2017. Microsimulation of an autonomous taxi-system in Munich, in: Models and Technologies for Intelligent Transportation Systems (MT-ITS), 2017 5th IEEE International Conference On. IEEE, pp. 833–838.

Davidson, P., Spinoulas, A., 2016. Driving Alone Versus Riding Together–How Shared Autonomous Vehicles Can Change the Way We Drive. Road Transp. Res. J. Aust. N. Z. Res. Pract. 25, 51.

Dia, H., Javanshour, F., 2017. Autonomous Shared Mobility-On-Demand: Melbourne Pilot Simulation Study. Transp. Res. Procedia 22, 285–296. https://doi.org/10.1016/j.trpro.2017.03.035

Duncan, G., 2010. From microsimulation to nanosimulation: visualizing person trips over multiple modes of transport. Transp. Res. Rec. J. Transp. Res. Board 130–137.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transp. Res. Part C Emerg. Technol. 40, 1–13.

Fiedler, D., Cáp, M., Certický, M., 2017. Impact of Mobility-on-Demand on Traffic Congestion: Simulation-based Study. CoRR abs/1708.02484.

Fournier, G., Pfeiffer, C., Baumann, M., Wörner, R., 2017. Individual Mobility by Shared Autonomous Electric Vehicle Fleets. Cost and CO2 comparison with internal combustion engine vehicles in Berlin, Germany. Presented at the 2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC), Funchal, Portugal.

Gawron, J.H., Keoleian, G.A., De Kleine, R.D., Wallington, T.J., Kim, H.C., 2018. Life Cycle Assessment of Connected and Automated Vehicles: Sensing and Computing Subsystem and Vehicle Level Effects. Environ. Sci. Technol. 52, 3249–3256.

Greenblatt, J.B., Saxena, S., 2015. Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. Nat. Clim. Change 2015, 860–863.

Gurumurthy, K.M., Kockelman, K.M., 2018. Analyzing the dynamic ride-sharing potential for shared autonomous vehicle fleets using cellphone data from Orlando, Florida. Comput. Environ. Urban Syst. 71, 177–185.

Hoogendoorn, S.P., Bovy, P.H., 2001. State-of-the-art of vehicular traffic flow modelling. Proc. Inst. Mech. Eng. Part J. Syst. Control Eng. 215, 283–303.

Hörl, S., 2017. Agent-based simulation of autonomous taxi services with dynamic demand responses. Procedia Comput. Sci. 109, 899–904. https://doi.org/10.1016/j.procs.2017.05.418

Hyland, M., Mahmassani, H.S., 2018. Dynamic autonomous vehicle fleet operations: Optimization-based strategies to assign AVs to immendiate travel demand requests. Transp. Res. Part C Emerg. Technol. 278–297.

Jalali, S., Wohlin, C., 2012. Systematic literature studies: database searches vs. backward snowballing, in: Proceedings of the ACM-IEEE International Symposium on Empirical Software Engineering and Measurement. ACM, pp. 29–38.

Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C Emerg. Technol. 69, 343–355. https://doi.org/10.1016/j.trc.2016.06.015

Litman, T., 2015. Autonomous Vehicle Implementation Predictions, in: Proceedings of the 2015 Transportation Research Board Annual Meeting, 15-3326.

Loeb, B., Kockelman, K.M., Liu, J., 2018. Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. Transp. Res. Part C Emerg. Technol. 89, 222–233. https://doi.org/10.1016/j.trc.2018.01.019

Lu, M., Taiebat, M., Xu, M., Hsu, S.-C., 2018. Multiagent Spatial Simulation of Autonomous Taxis for Urban Commute: Travel Economics and Environmental Impacts. J. Urban Plan. Dev. 144, 04018033. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000469

MacKenzie, D., Wadud, Z., Leiby, P., 2014. A first order estimate of energy impacts of automated vehicles in the united states, in: Transportation Research Board 93rd Annual Meeting. Washington.

Marczuk, K., Soh, H., Azevedo, C.M.L., Lee, D.-H., Frazzoli, E., 2016. Simulation Framework for Rebalancing of Autonomous Mobility on Demand Systems. MATEC Web Conf 81, 01005. https://doi.org/10.1051/matecconf/20168101005

May, A.D., 1990. Traffic flow fundamentals.

Merlin, L.A., 2017. Comparing Automated Shared Taxis and Conventional Bus Transit for a Small City. J. Public Transp. 20, 2.

Meyer, J., Becker, H., Bösch, P.M., Axhausen, K.W., 2017. Autonomous vehicles: The next jump in accessibilities? Res. Transp. Econ.

Milakis, D., Snelder, M., van Arem, B., Homem de Almeida Correia, G., van Wee, G.P., 2017. Development and transport implications of automated vehicles in the Netherlands: scenarios for 2030 and 2050. Eur. J. Transp. Infrastruct. Res. 17, 63–85.

OECD International Transport Forum, 2015. Urban Mobility System Upgrade - How shared self-driving cars could change city traffic.

Pernestål Brenden, A., Kottenhof, K., 2018. Self-driving shuttles as a complement to public transport – a characterization and classification, in: Proceedings of Transport Research Arena TRA 2018. Presented at the Transport Research Arena TRA 2018, Vienna, Austria.

Pernestål Brenden, A., Kristoffersson, I., Mattsson, L.-G., 2017. Where will self-driving vehicles take us? Scenarios for the development of automated vehicles with Sweden as a case study, in: Proceedings of the European Transport Conference. Barcelona.

SAE International, 2016. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles [WWW Document]. URL http://standards.sae.org/j3016_201609/ (accessed 9.11.17).

Shen, W., Lopes, C., 2015. Managing autonomous mobility on demand systems for better passenger experience, in: Chen Q., Torroni P., Villata S., Hsu J., Omicini A. (Eds) PRIMA 2015: Principles and Practice of Multi-Agent Systems. PRIMA 2015. Lecture Notes in Computer Science, Vol 9387. Springer, Cham.

Townsend, A., 2014. Re-programming Mobility - The Digital Transformation of Transportation in the United States. NYU Wagner Rudin Center for Transportation Policy and Management.

Truong, L.T., De Gruyter, C., Currie, G., Delbosc, A., 2017. Estimating the Trip Generation Impacts of Autonomous Vehicles on Car Travel in Victoria, Australia. Transportation 44, 1279–1292.

van den Berg, V.A., Verhoef, E.T., 2016. Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. Transp. Res. Part B Methodol. 94, 43–60.

Wee, B.V., Banister, D., 2016. How to Write a Literature Review Paper? Transp. Rev. 36, 278–288. https://doi.org/10.1080/01441647.2015.1065456

Winter, K., Cats, O., Correia, G.H. de A., Arem, B. van, 2016. Designing an Automated Demand-Responsive Transport System: Fleet Size and Performance Analysis for a Campus–Train Station Service. Transp. Res. Rec. J. Transp. Res. Board 2542, 75–83.

Yap, M.D., Correia, G., Arem, B. van, 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transp. Res. Policy Pract. 1–16.

Ye, L., Yamamoto, T., 2018. Modeling connected and autonomous vehicles in heterogeneous traffic flow. Phys. Stat. Mech. Its Appl. 490, 269–277.

Zhang, R., Spieser, K., Frazzoli, E., Pavone, M., 2015. Models, algorithms, and evaluation for autonomous mobility-on-demand systems, in: American Control Conference (ACC), 2015. IEEE, pp. 2573–2587.

Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015. Exploring the impact of shared autonomous vehicles on parking demand: An agent-based simulation approach. Sustain. Cities Soc. 34–45.